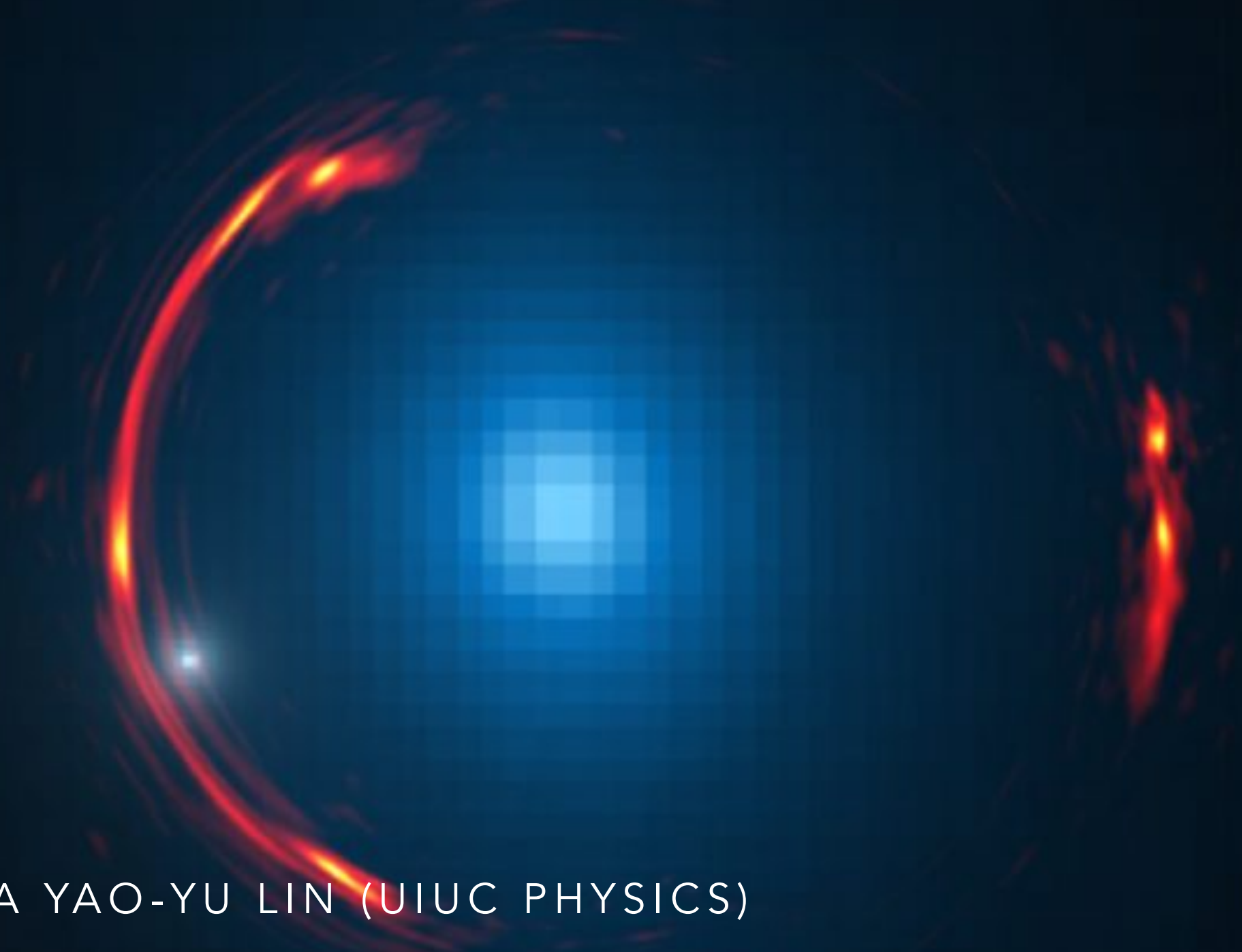


# HUNTING FOR DARK MATTER SUBSTRUCTURES IN STRONG LENSING WITH NEURAL NETWORKS



JOSHUA YAO-YU LIN (UIUC PHYSICS)

MACHINE LEARNING FOR PHYSICS AND THE PHYSICS OF LEARNING  
WORKSHOP, IPAM UCLA | 2019.9.26

Lin et al. 2019 (In prep)

PEOPLE I WORK WITH

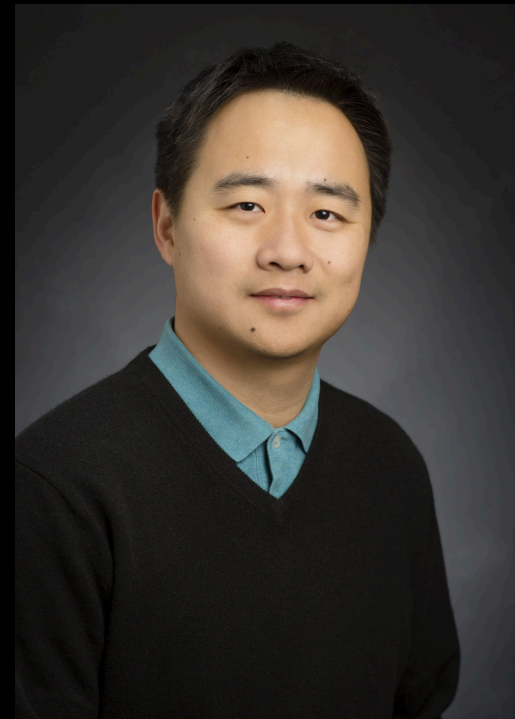
# LOCAL GROUP



Hang Yu  
[UIUC]



Warren  
Morningstar  
[Stanford]

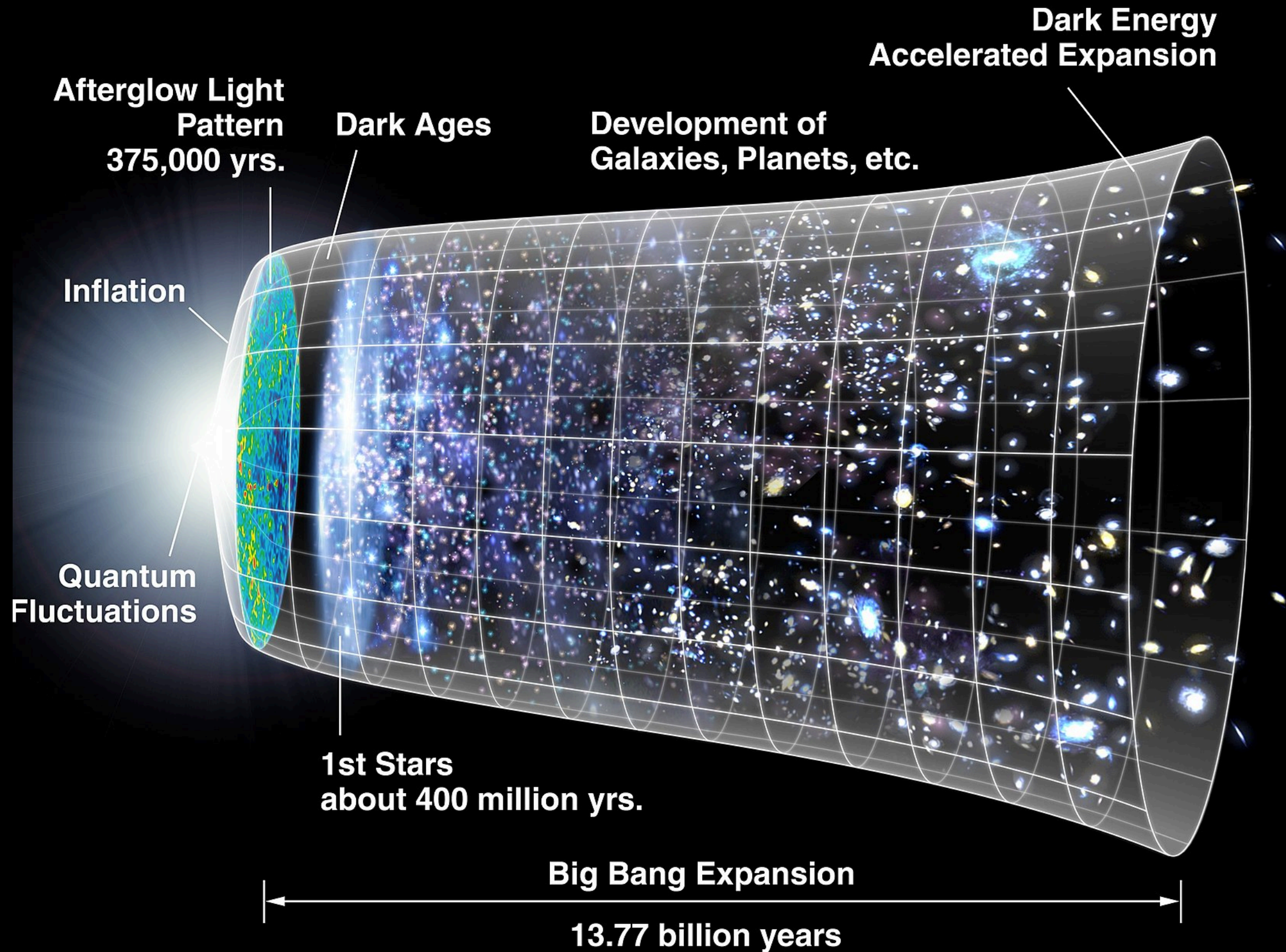


Jian Peng  
[CS@UIUC]



Gil Holder  
[UIUC]



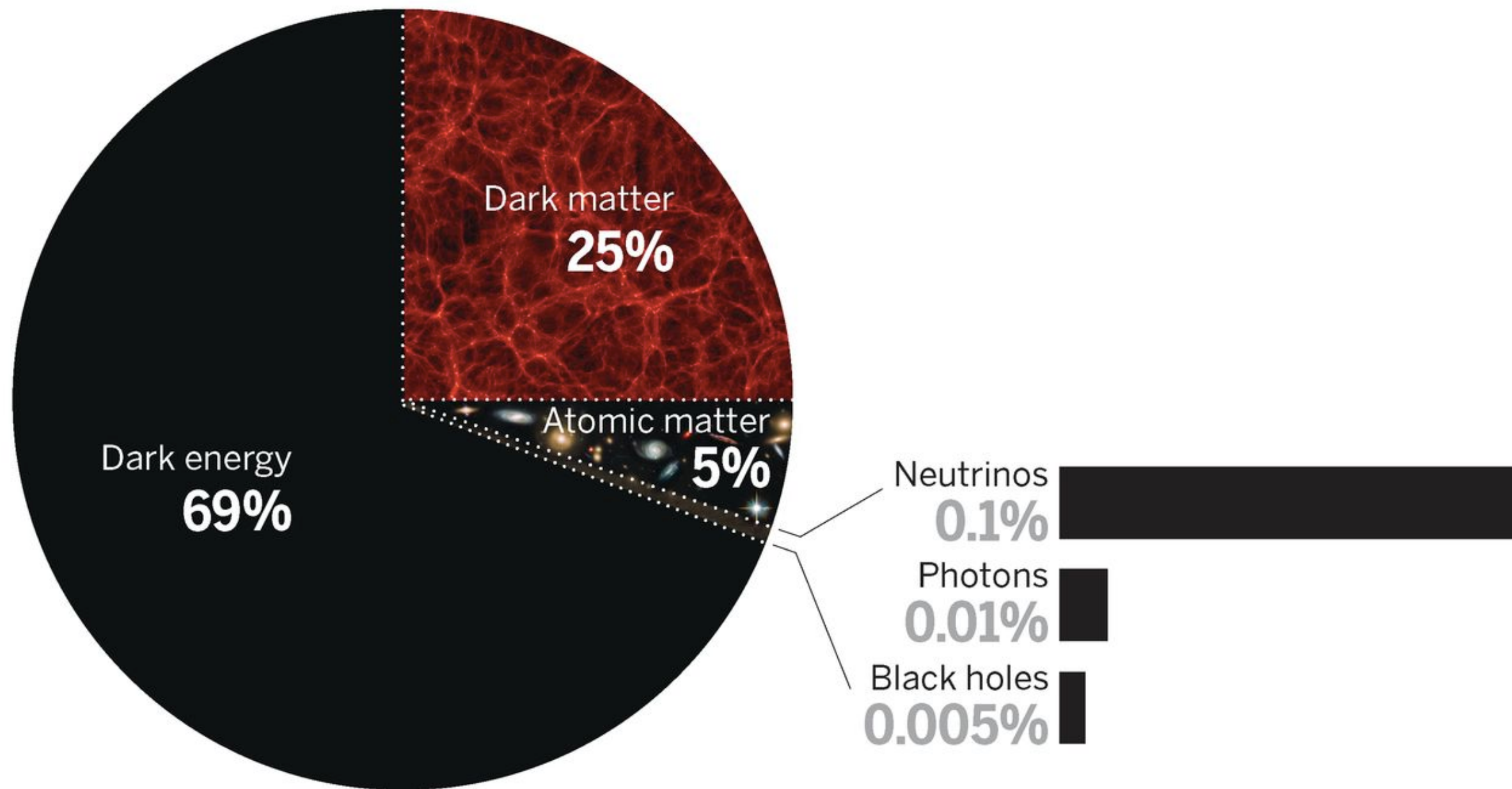


**Image Credit: NASA/WMAP**



# The multiple components that compose our universe

Current composition (as the fractions evolve with time)



Three different types of neutrinos comprise at least 0.1%, the cosmic background radiation makes up 0.01%, and black holes comprise at least 0.005%.

David Spergel (Science, 2015)



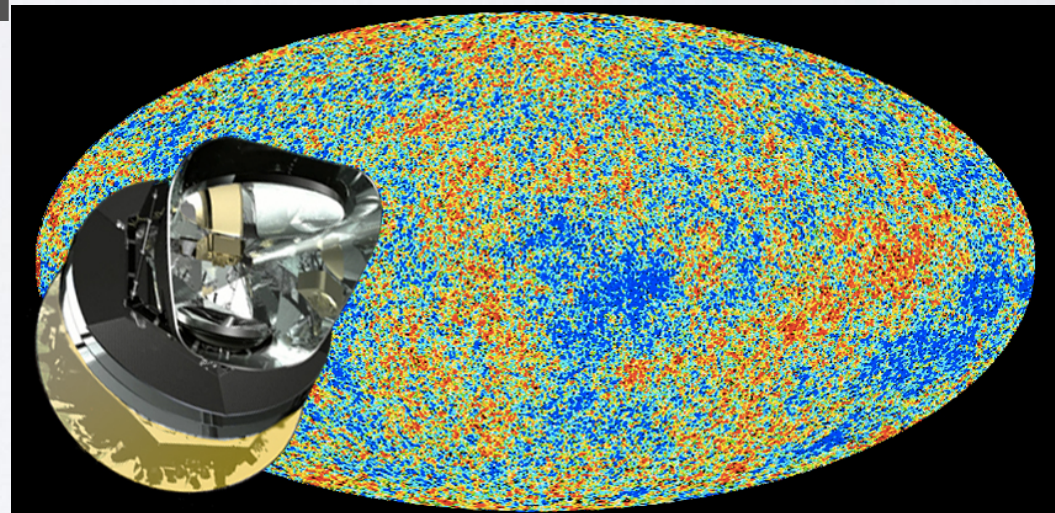
# Dark Matter

- 84% of the matter is Dark(DM)
- DM interacts through gravity.
- Further DM interactions unobserved so far. Such couplings must be very weak, much weaker than weak interactions.



# PROPERTY OF DM?

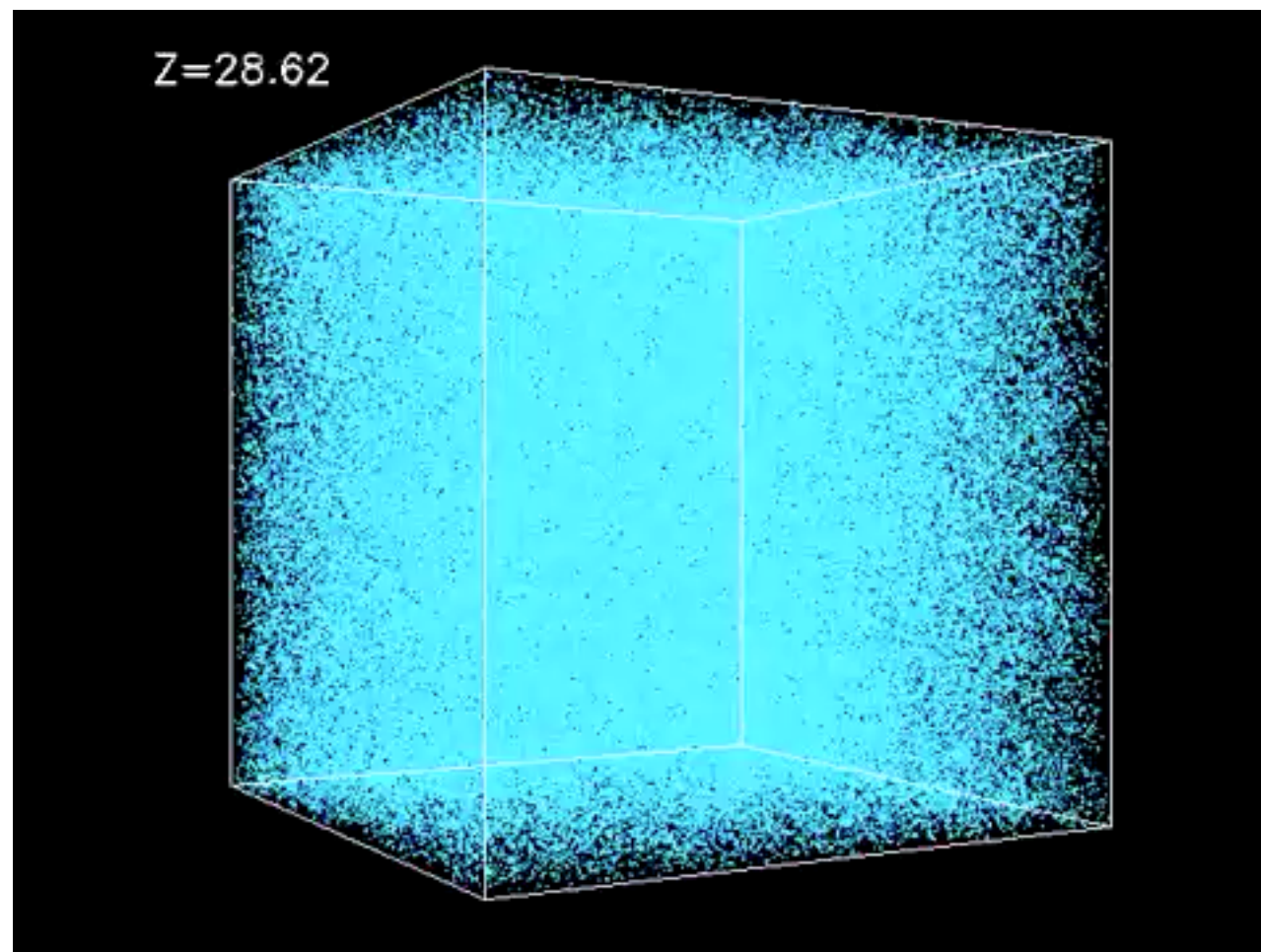
- Early time evolution (linear regime): **Cosmological Perturbation Theory** [See Modern Cosmology by S. Dodelson, or CP Ma, E Bertschinger arXiv: 9506072]: **cosmic microwave background**



- Late time evolution (Non-linear): **N-Body Simulation:**  
**Large-scale structure**

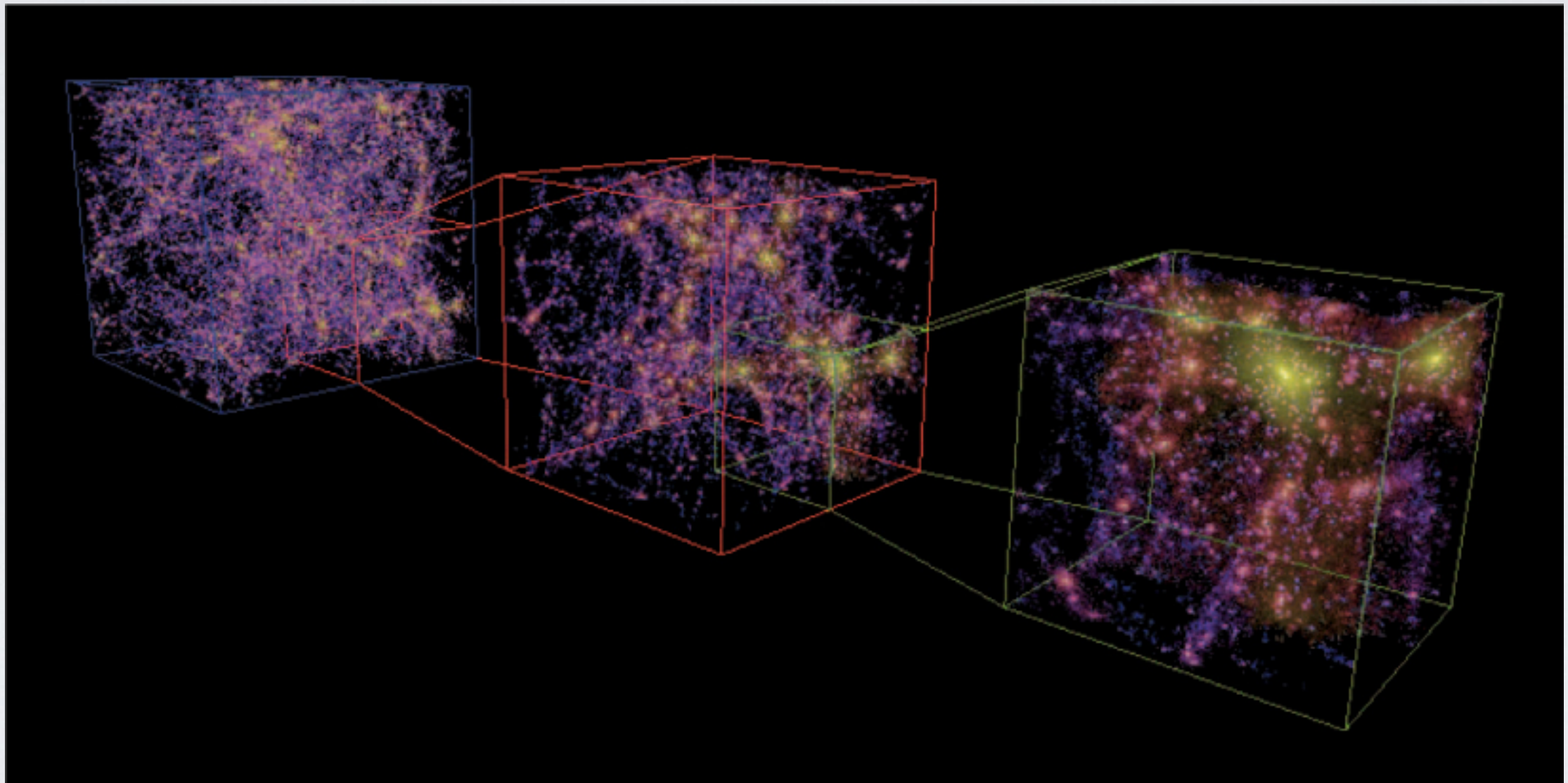


# N-Body Simulation of Cold Dark Matter



**Simulation by Andrey Kravtsov (The University of Chicago) and  
Anatoly Klypin (New Mexico State University)**

# N-BODY SIMULATION: DARK MATTER





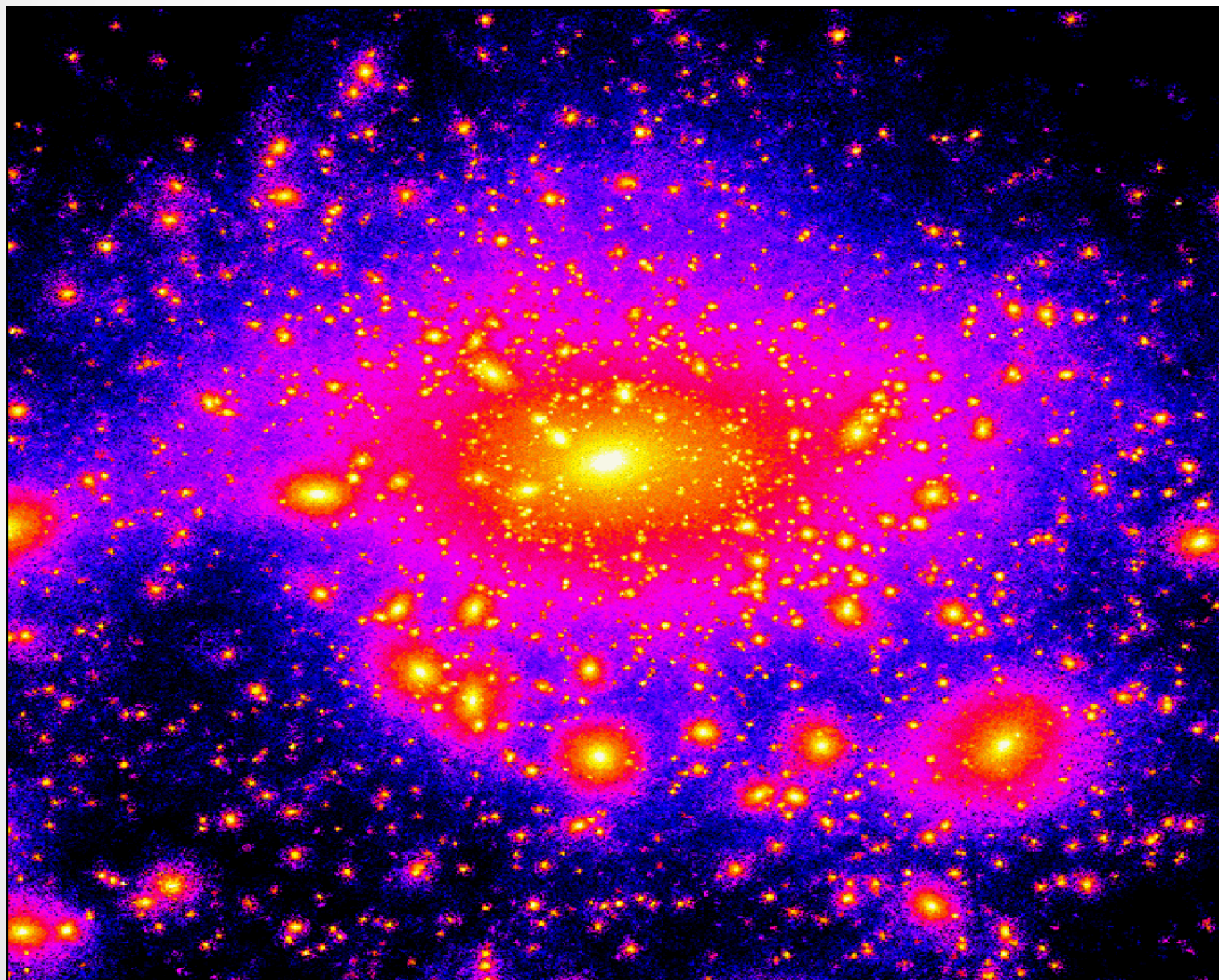
# N-Body Simulation on Cold Dark Matter

**In various cosmological N-body simulation, the  $\Lambda$  Cold Dark Matter ( $\Lambda$ CDM) model perform well especially on the large scale structure. (e.g. Millennium Run 2005)!**

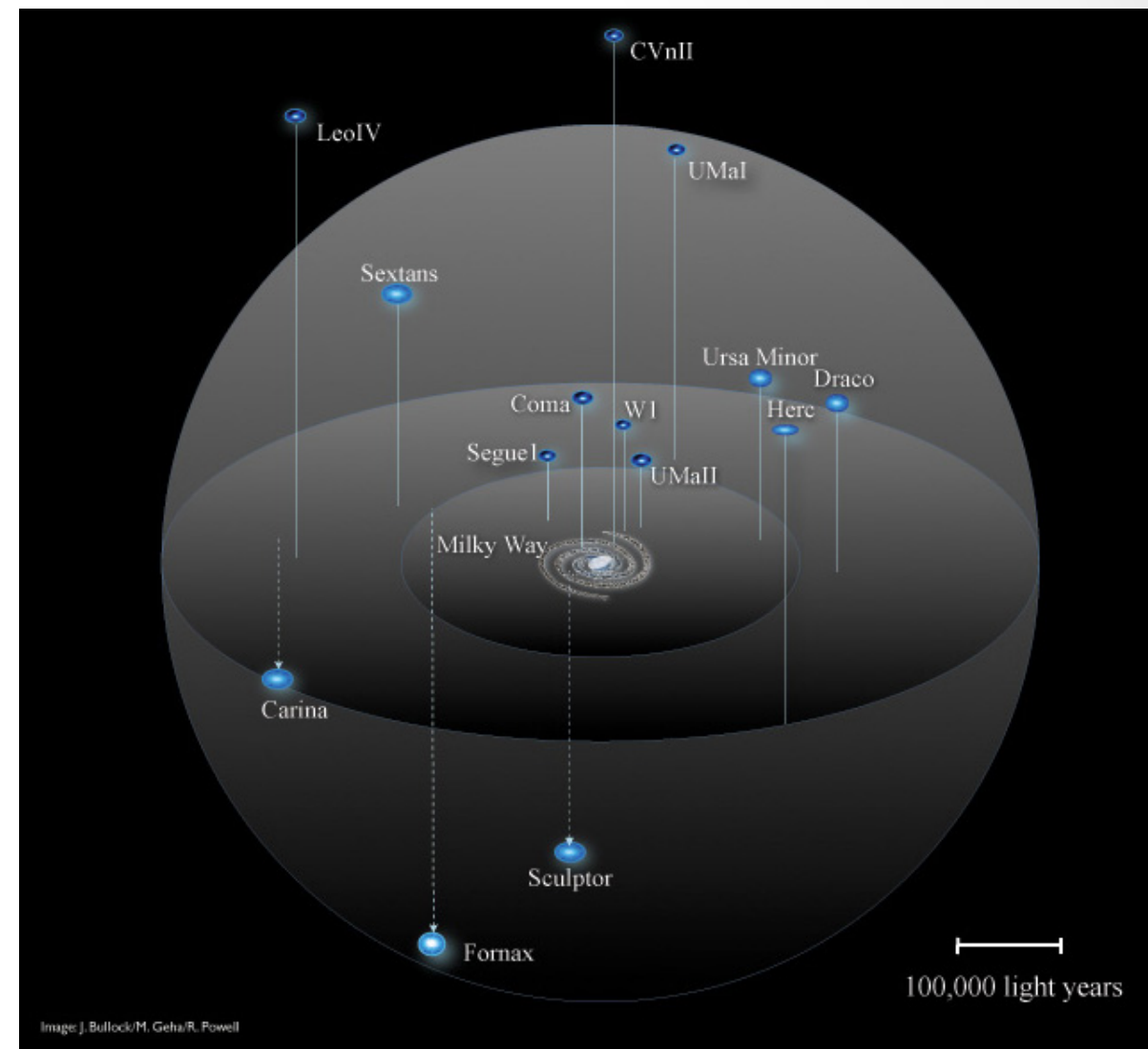
Max-Planck-Institut für Astrophysik (2005)



# Missing Satellites Problem



CDM Simulation (Mayer and Kazantzidis)



Satellite galaxies of the Milky Way (Observation)

Credit: J. Bullock, M. Geha, R. Powell



# Strong lensing: Natural place to probe dark matter substructures

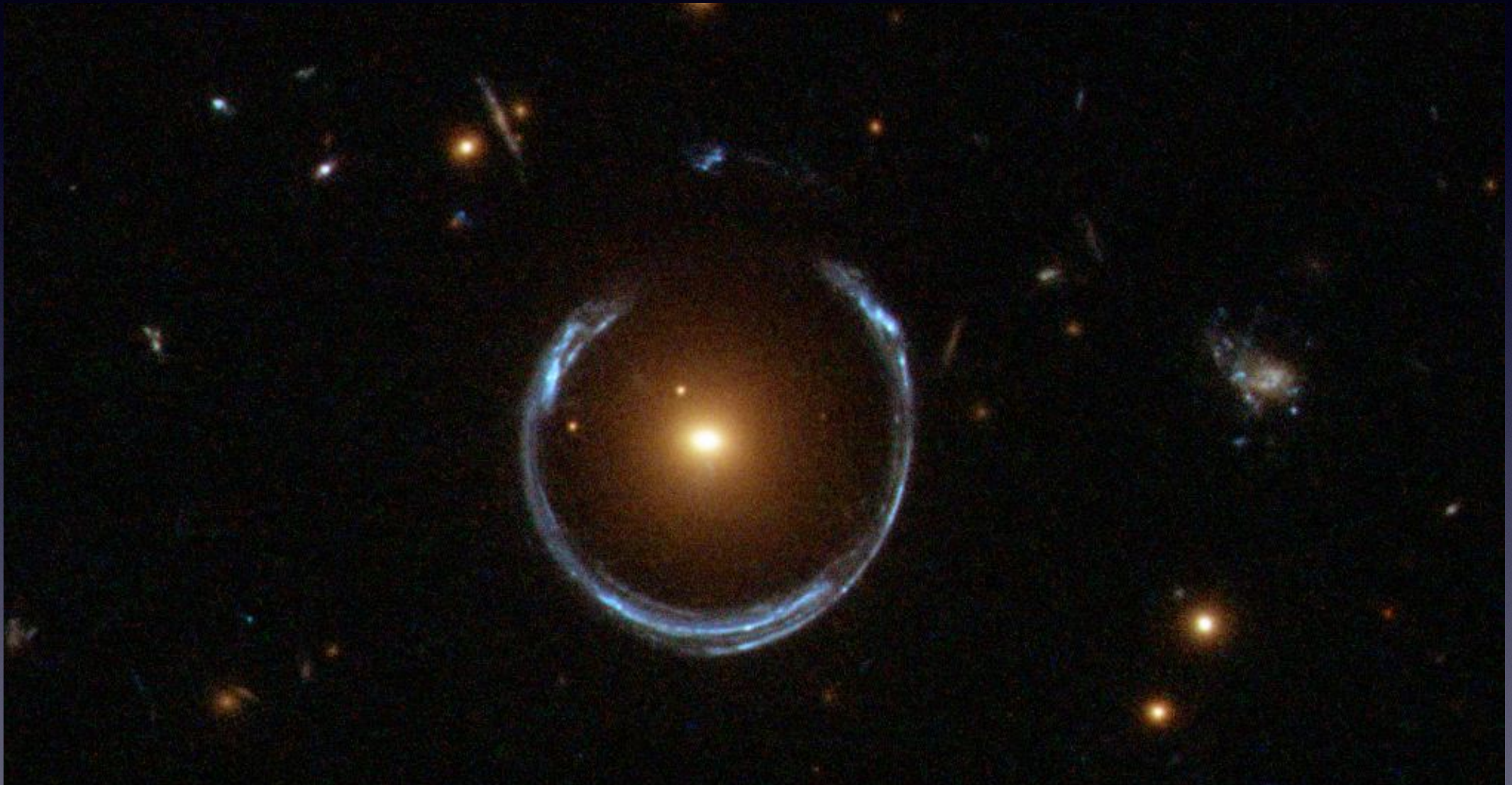
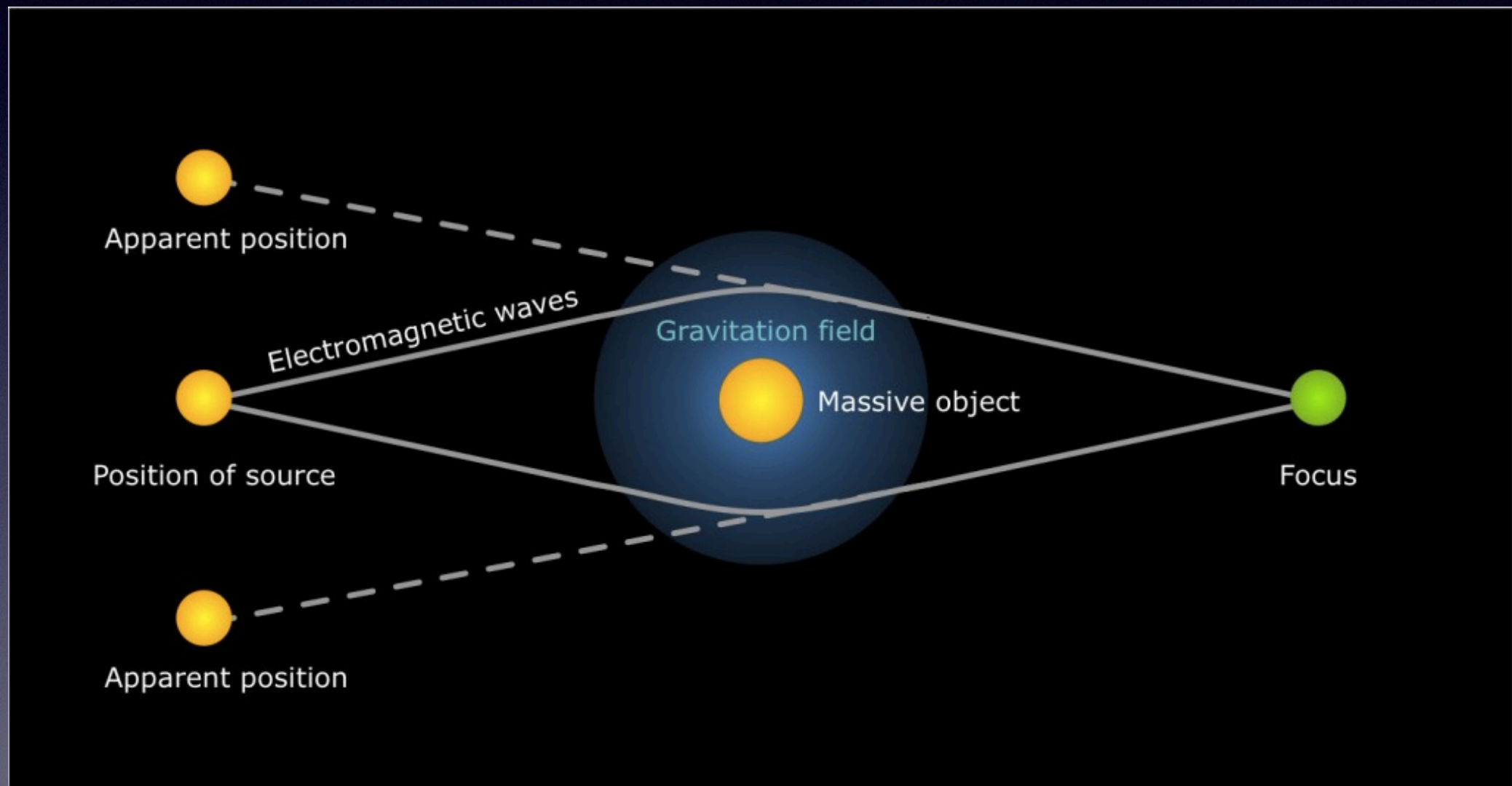


Image credit: ESA/Hubble & NASA



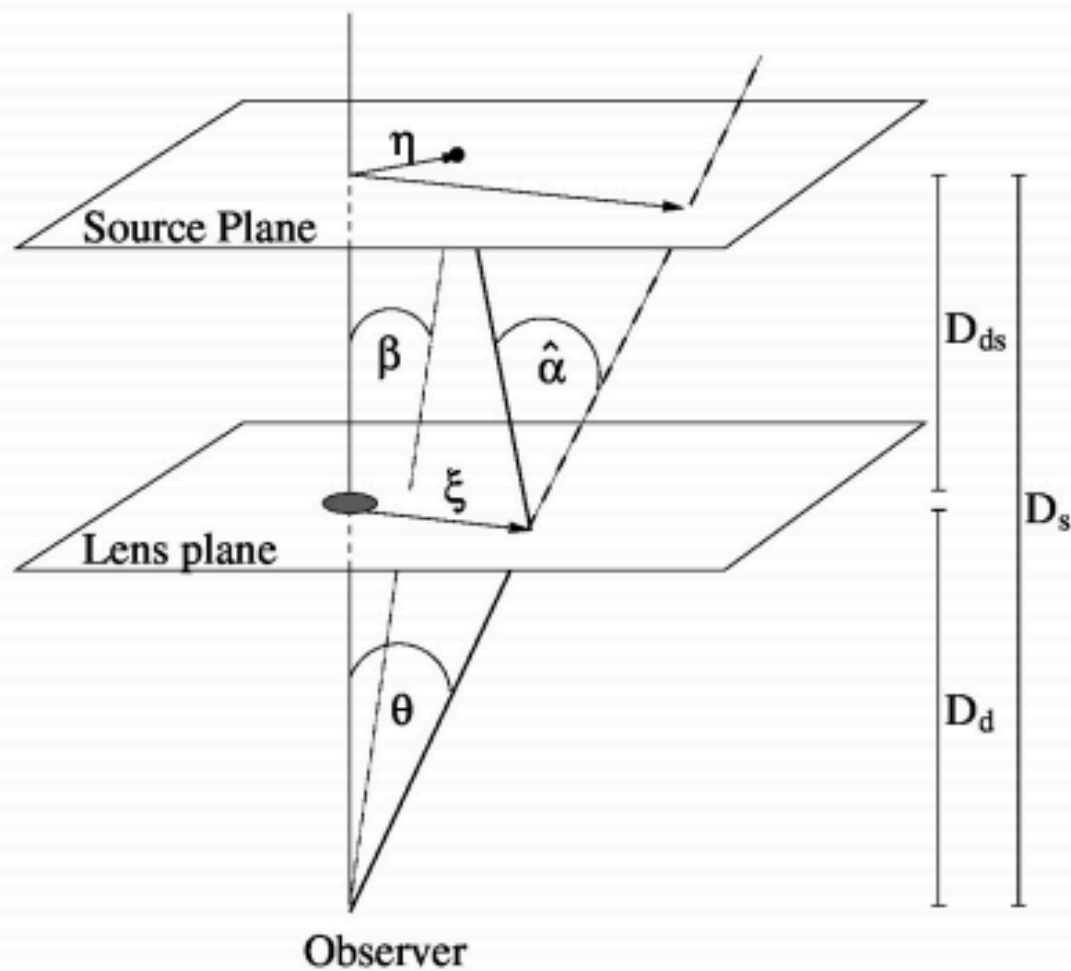
# Strong lensing





# Lensing basic

## Lens equation



$$\eta = \frac{D_s}{D_d} \xi - D_{ds} \hat{\alpha}(\xi)$$

In terms of angular coord.:

$$\eta = D_s \beta$$

$$\xi = D_d \theta$$

$$\beta = \theta - \alpha(\theta)$$

where

$$\alpha(\theta) = \frac{D_{ds}}{D_s} \hat{\alpha}(D_d \theta)$$

[Schneider et al. 2006]

# Lensing basic: caustic & critical curve

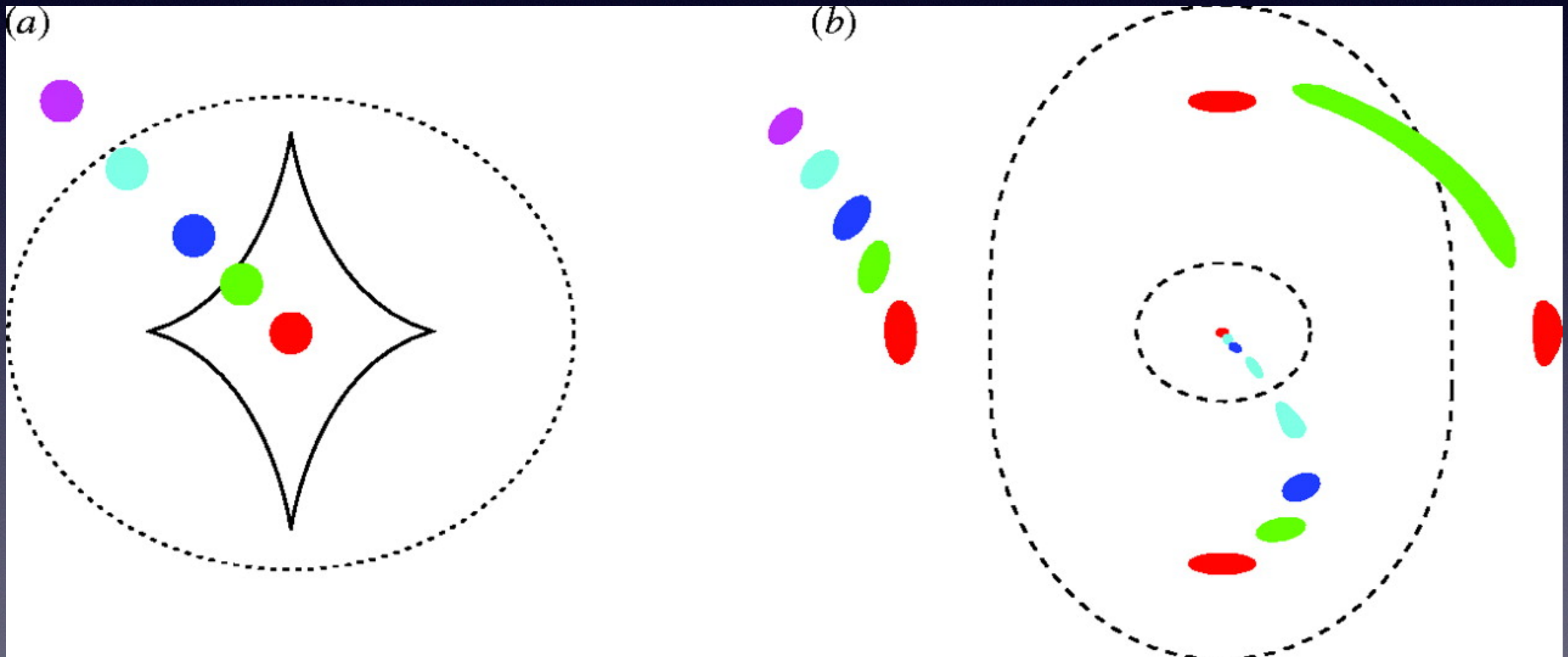
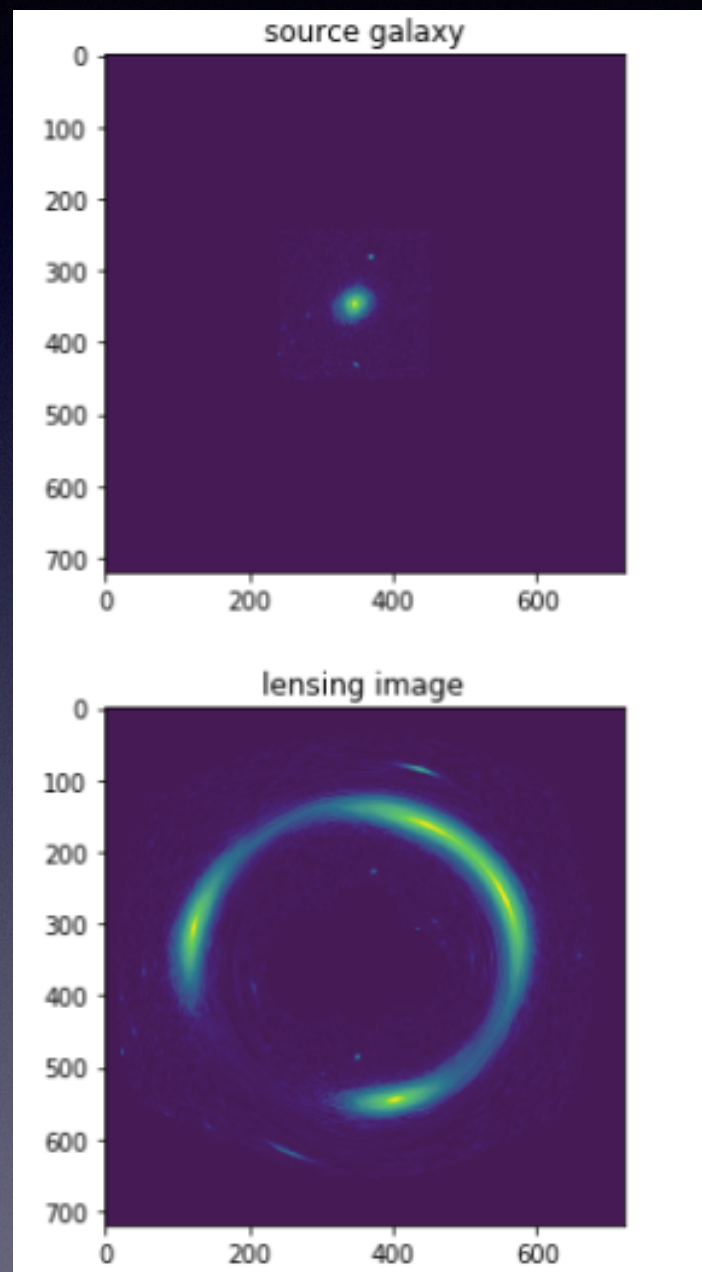
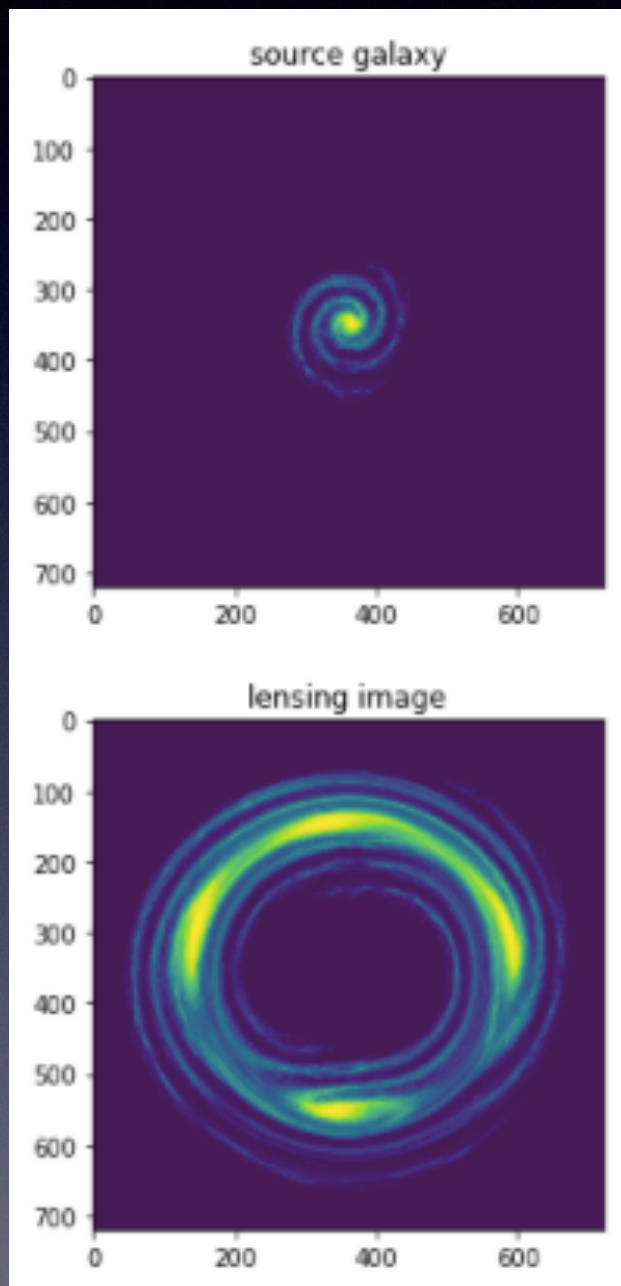


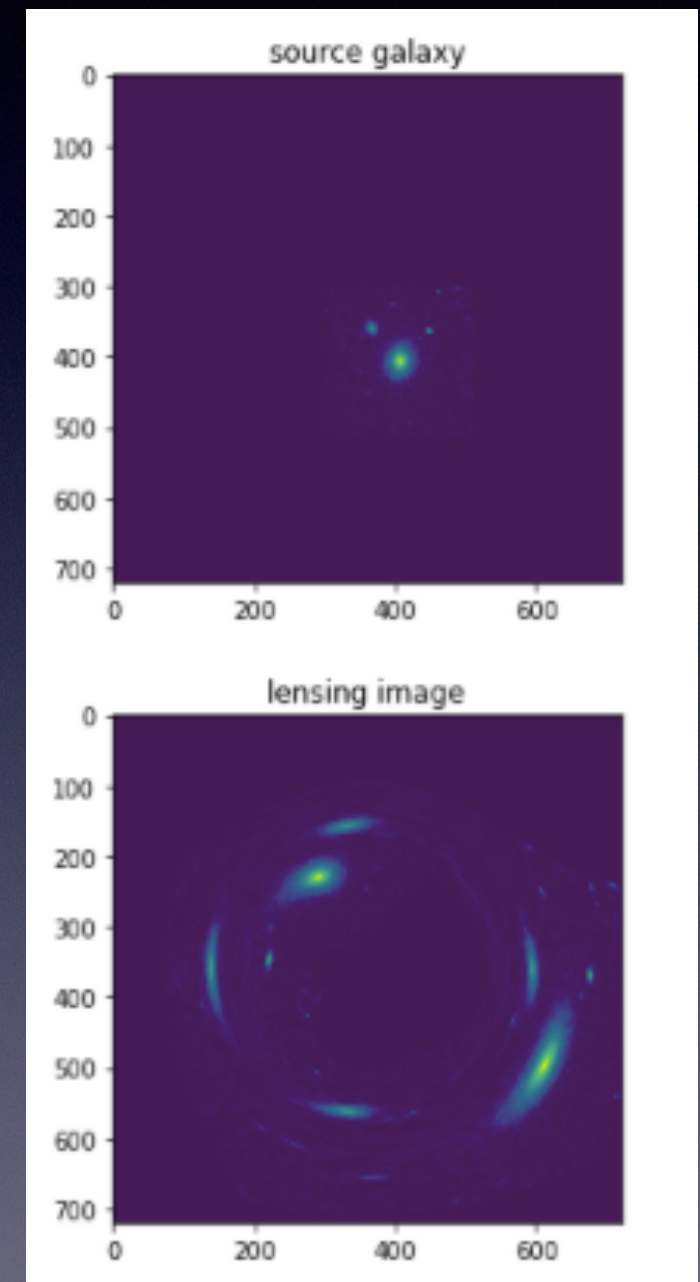
Figure from Narayan & Bartelmann (1995)



# Strong lensing simulations



Lensing image

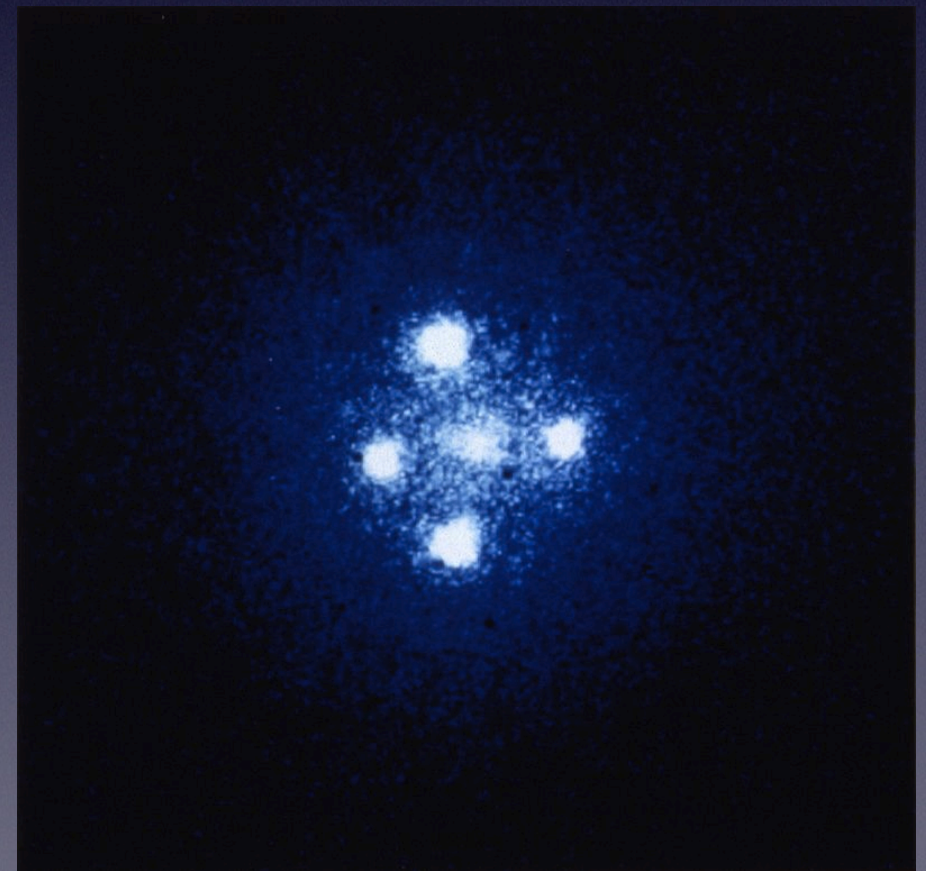
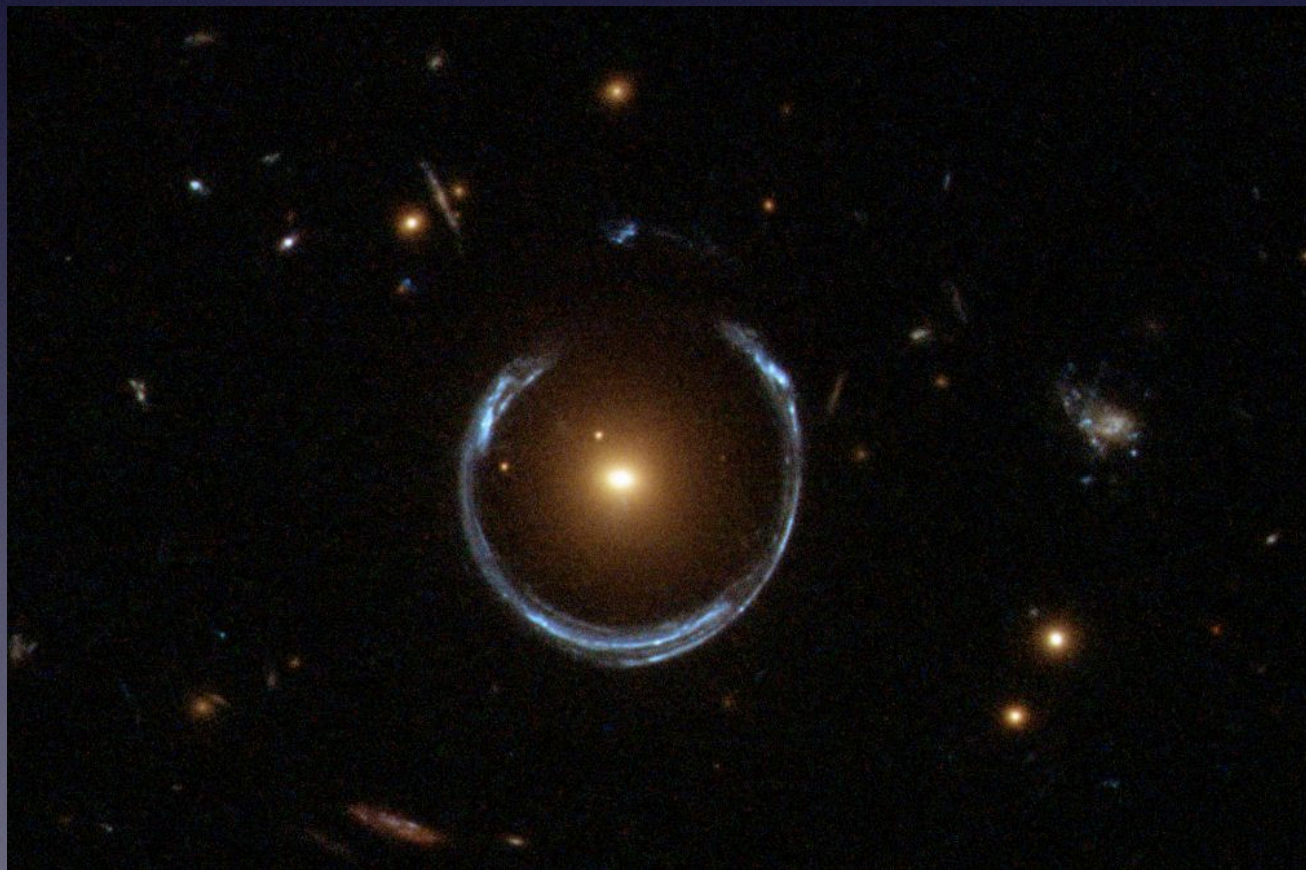


Lensing image



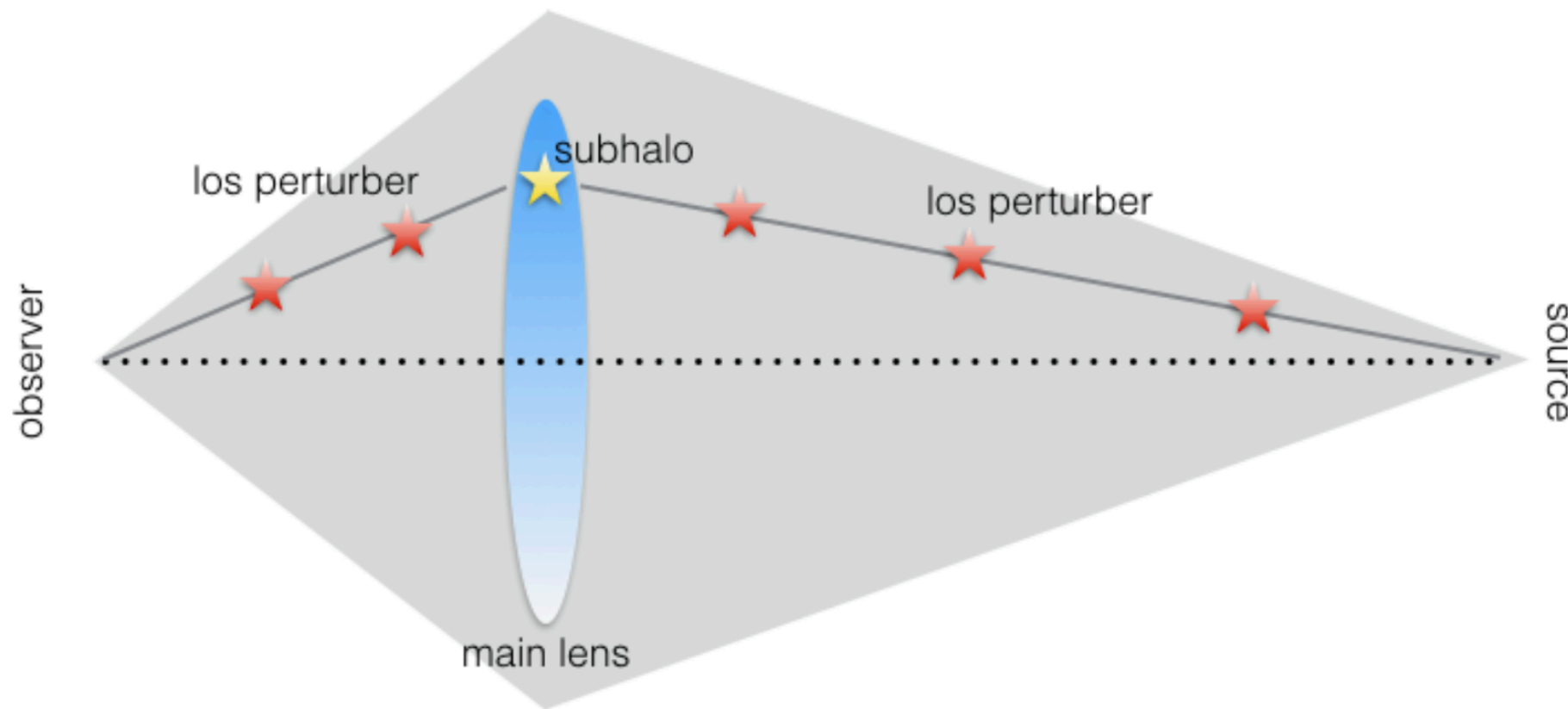
# Strong lensing for subhalos: Two approaches

- gravitational imaging vs flux ratio anomalies





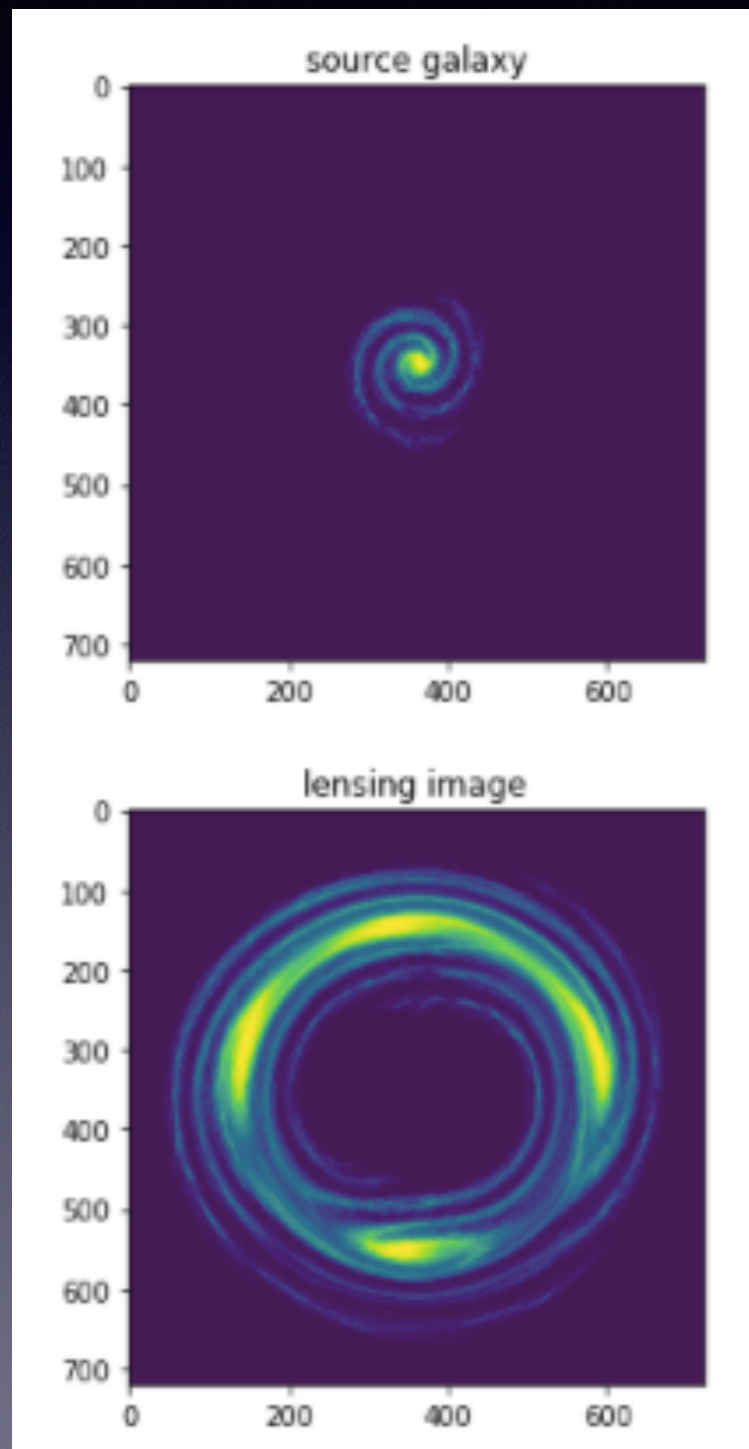
# Subhalo detection



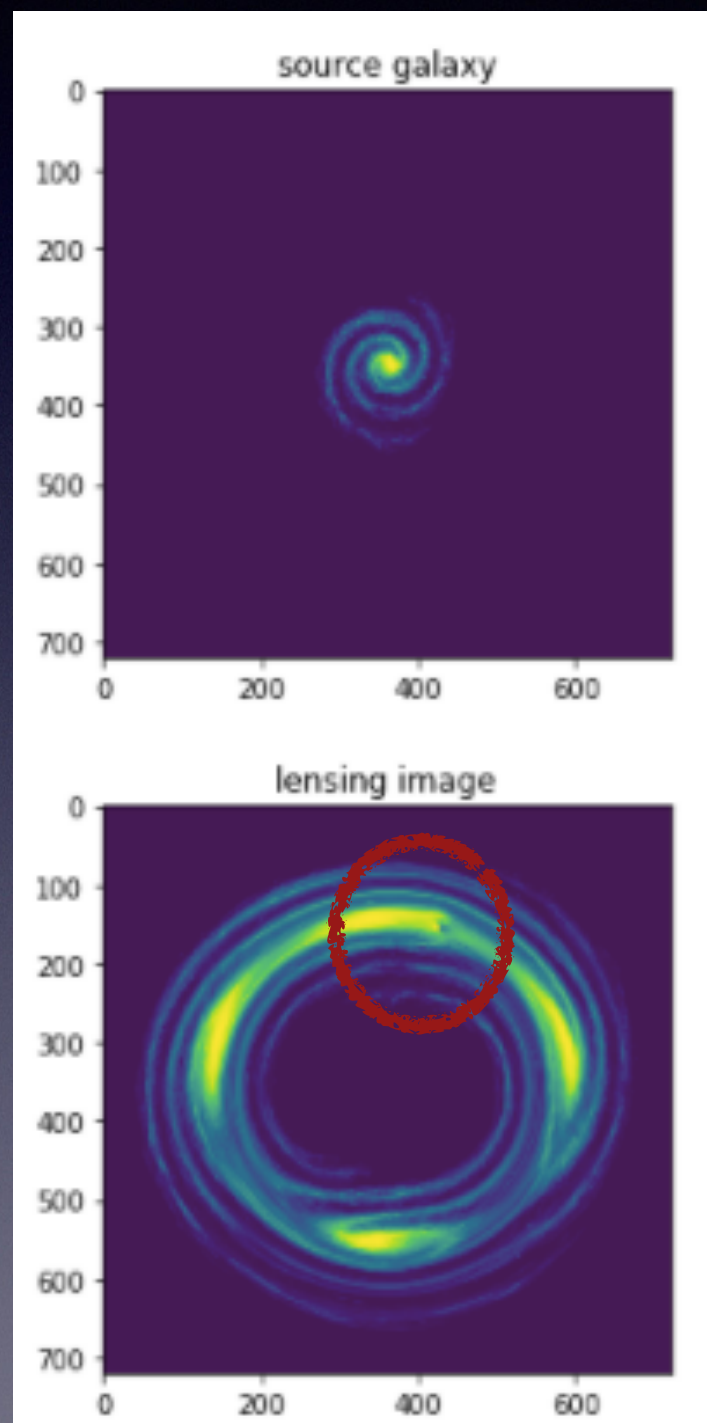
**Figure 2.** A simple sketch of the method we used to create our mock data; subhaloes and line-of-sight haloes are placed so that their lensing effect lies in the same projected position on the plane of the main lens; the grey region gives an example of the line-of-sight volume that is taken into account.



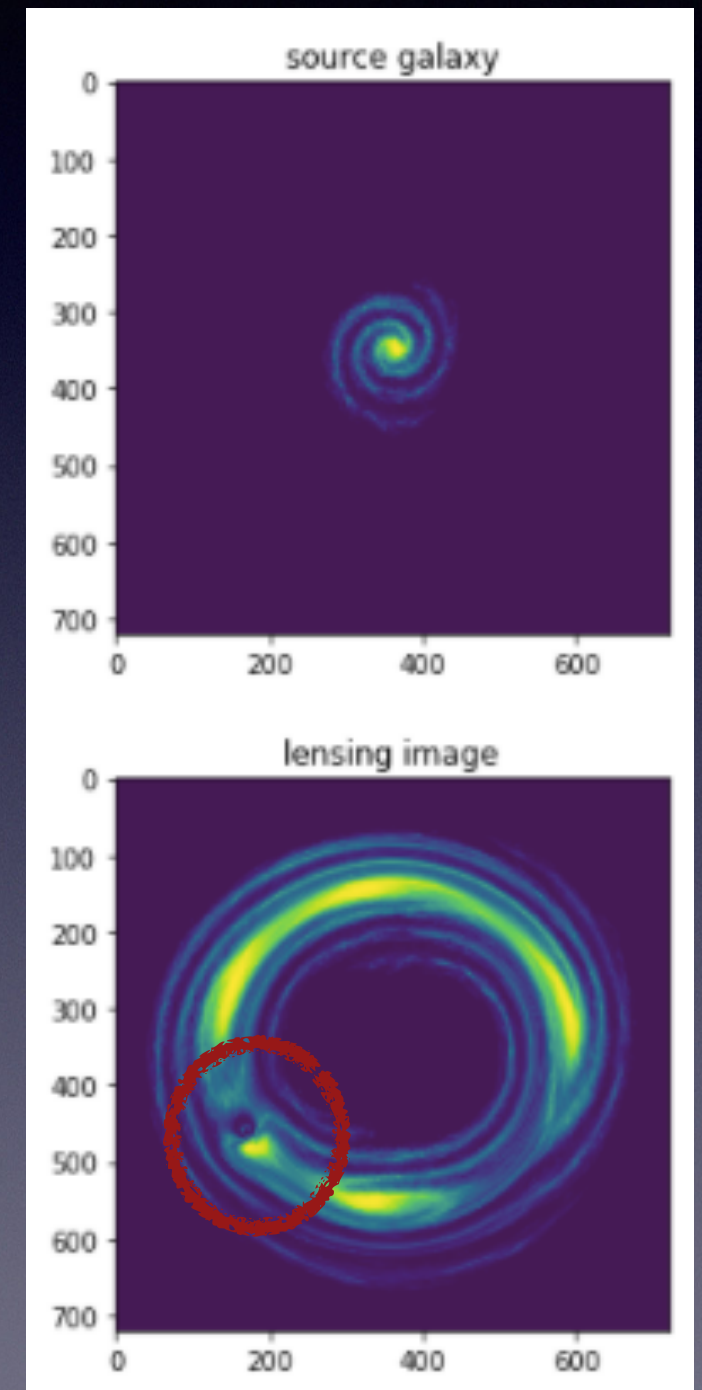
# Strong lensing with substructure as perturber



Smooth Lensing



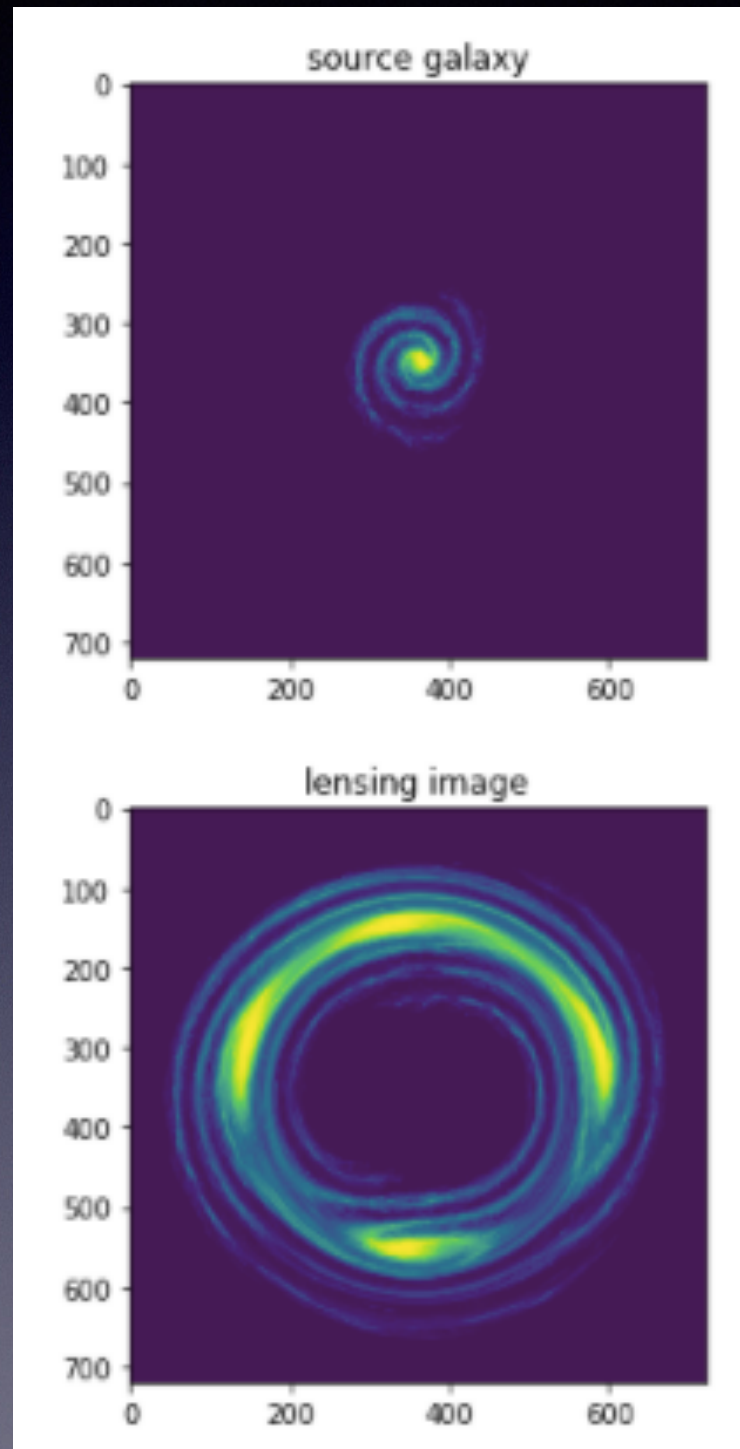
Lensing with perturber



Lensing with (large)  
massive perturber



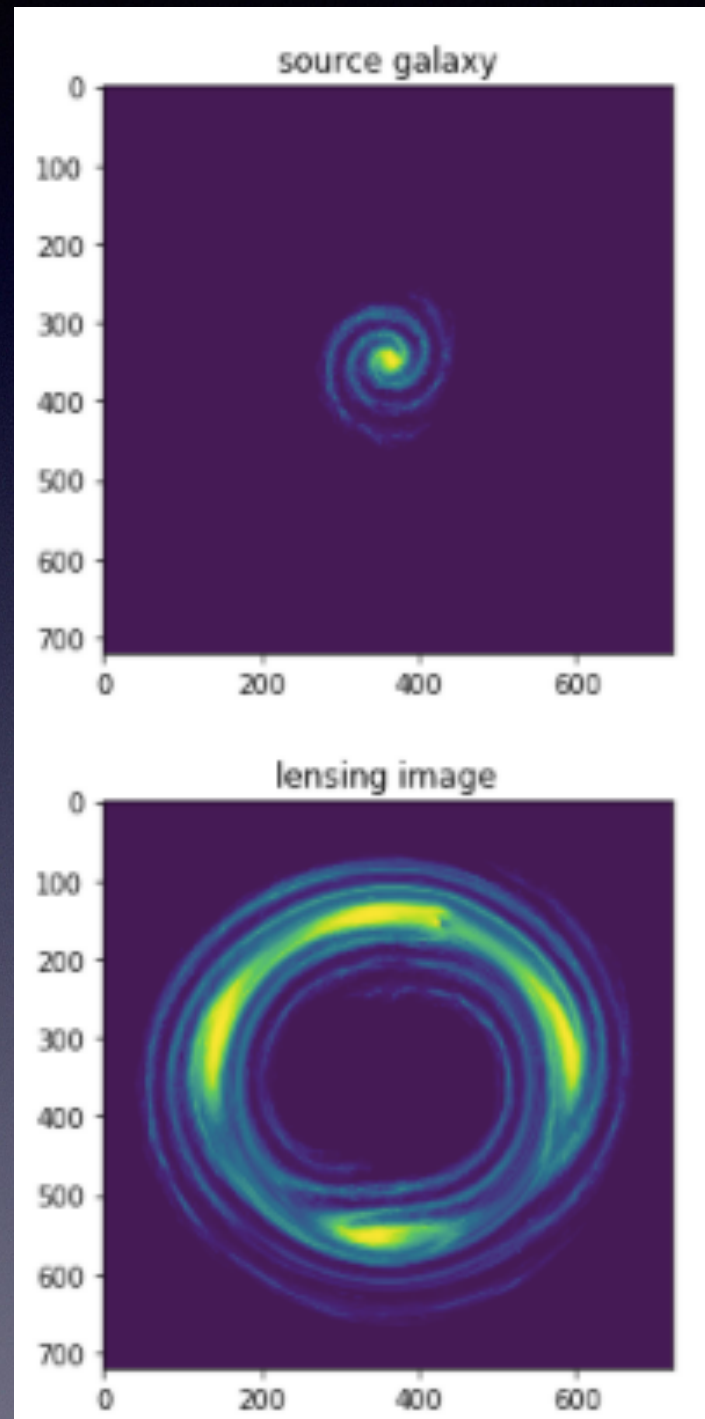
# Strong lensing with substructure as perturber



Smooth Lensing



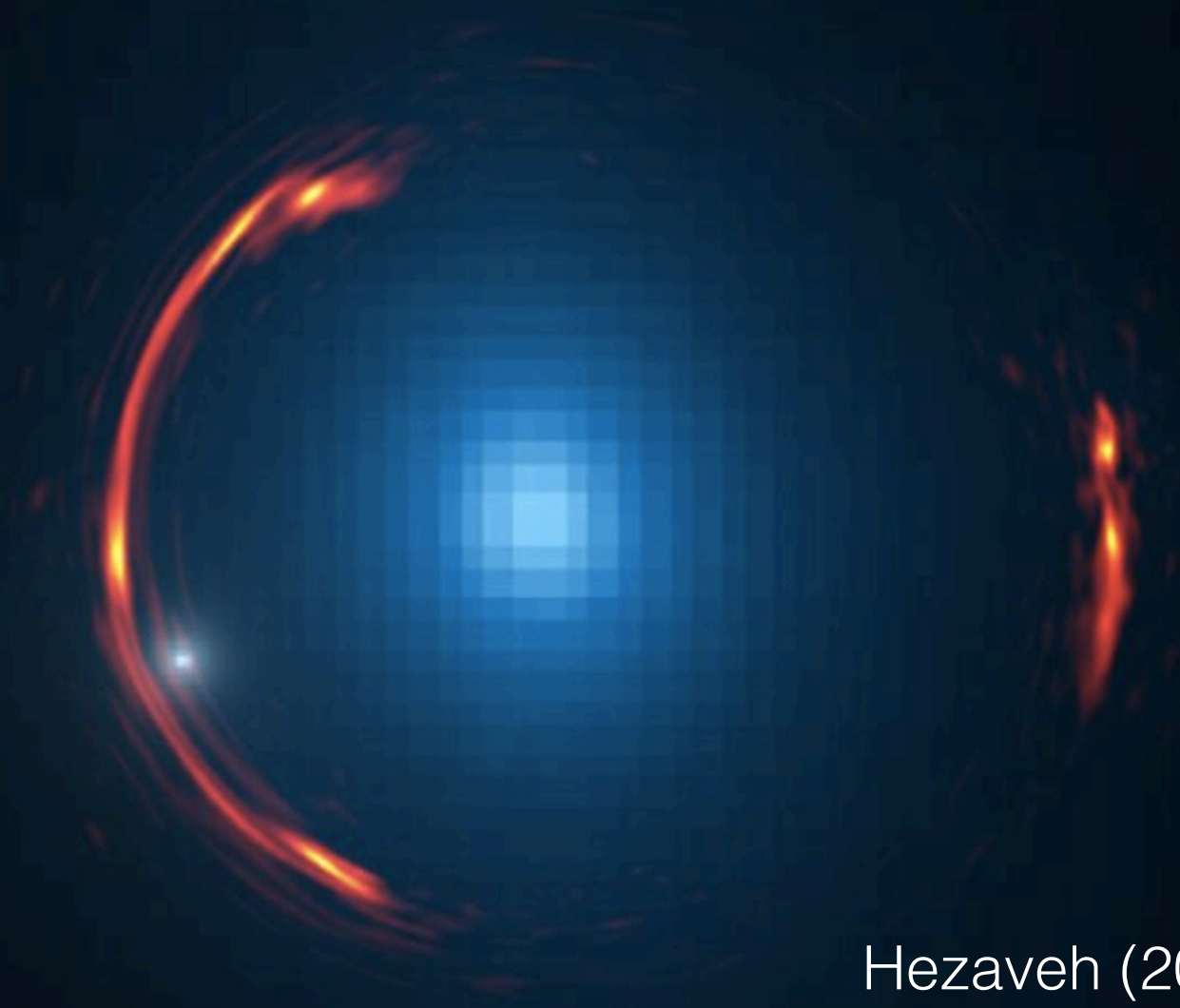
# Strong lensing with substructure as perturber



Lensing with perturber

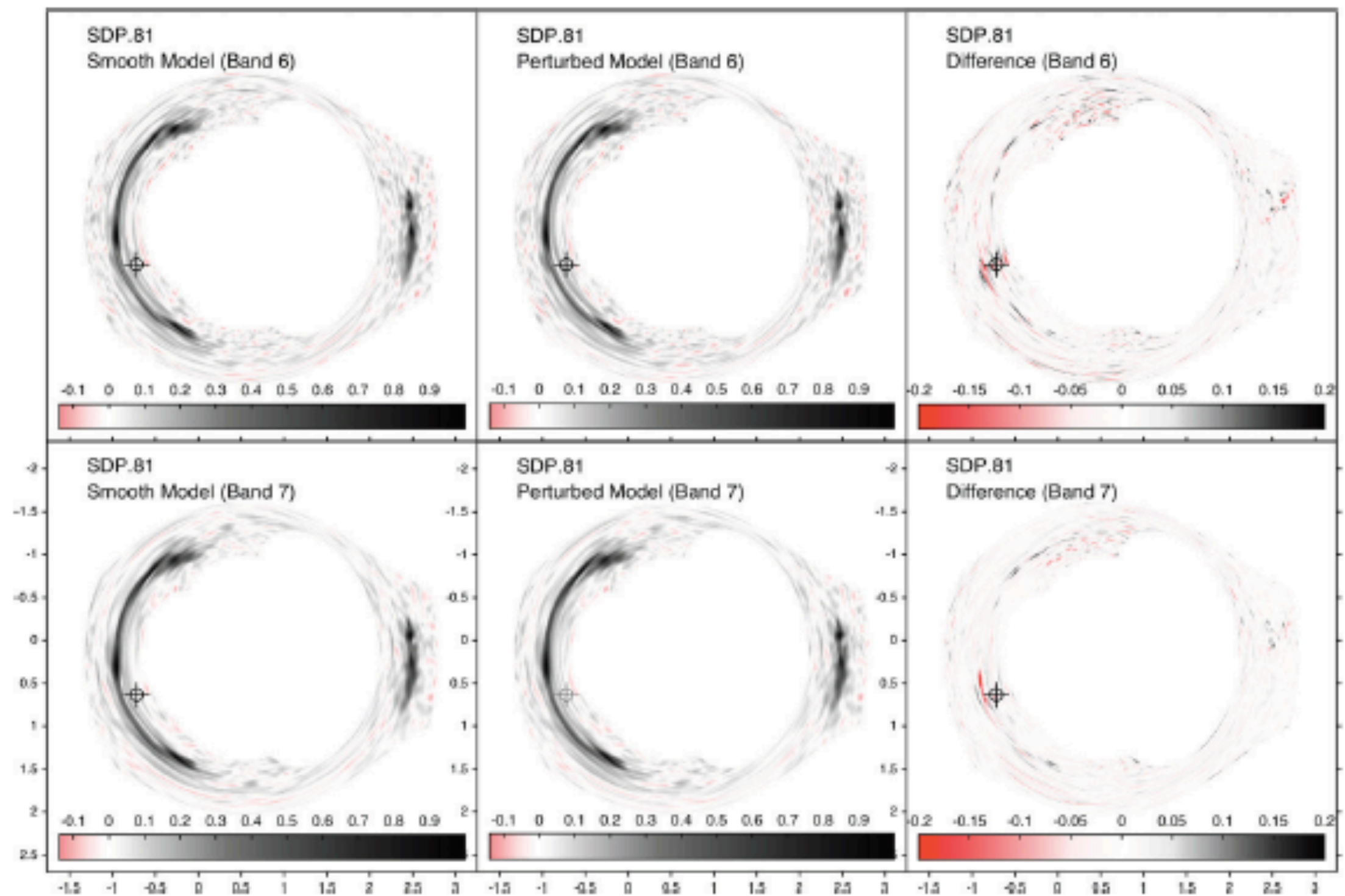


# Subhalo Hidden in ALMA Gravitational Lens Image



Hezaveh (2016) ArXiv:1601.01388





**Figure 6.** Top left: the sky emission model in band 6 for the best-fit smooth lens parameters for the SDP.81 data. Top middle: the same for the perturbed model. Top right: the difference between the two models. The bottom panels show the same for band 7. The bright feature in the difference plots is mainly caused by the astrometric anomaly of the arc. In each row, the images have been scaled to the peak flux of the smooth model.

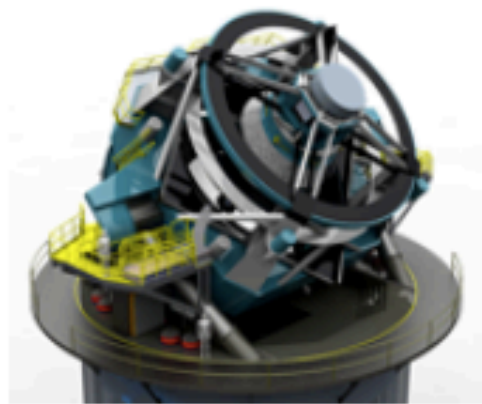


# LOOKING INTO THE FUTURE:

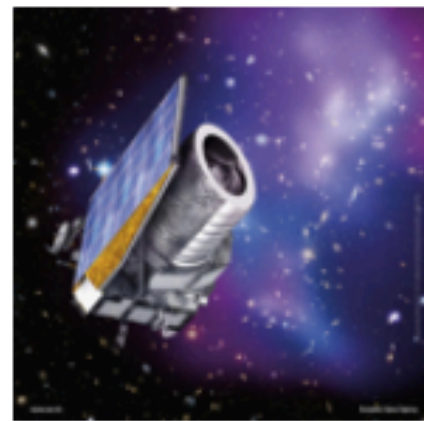
## New **Lenses**

For future surveys we find that, assuming Poisson limited lens galaxy subtraction, searches of the DES, LSST, and Euclid data sets should discover **2400**, **120000**, and **170000** galaxy–galaxy strong lenses, respectively

Collett, ApJ. 2015



**LSST**



euclid  
consortium



Looking into the future:

## Methods?

How are we going to analyze 170,000 lenses?

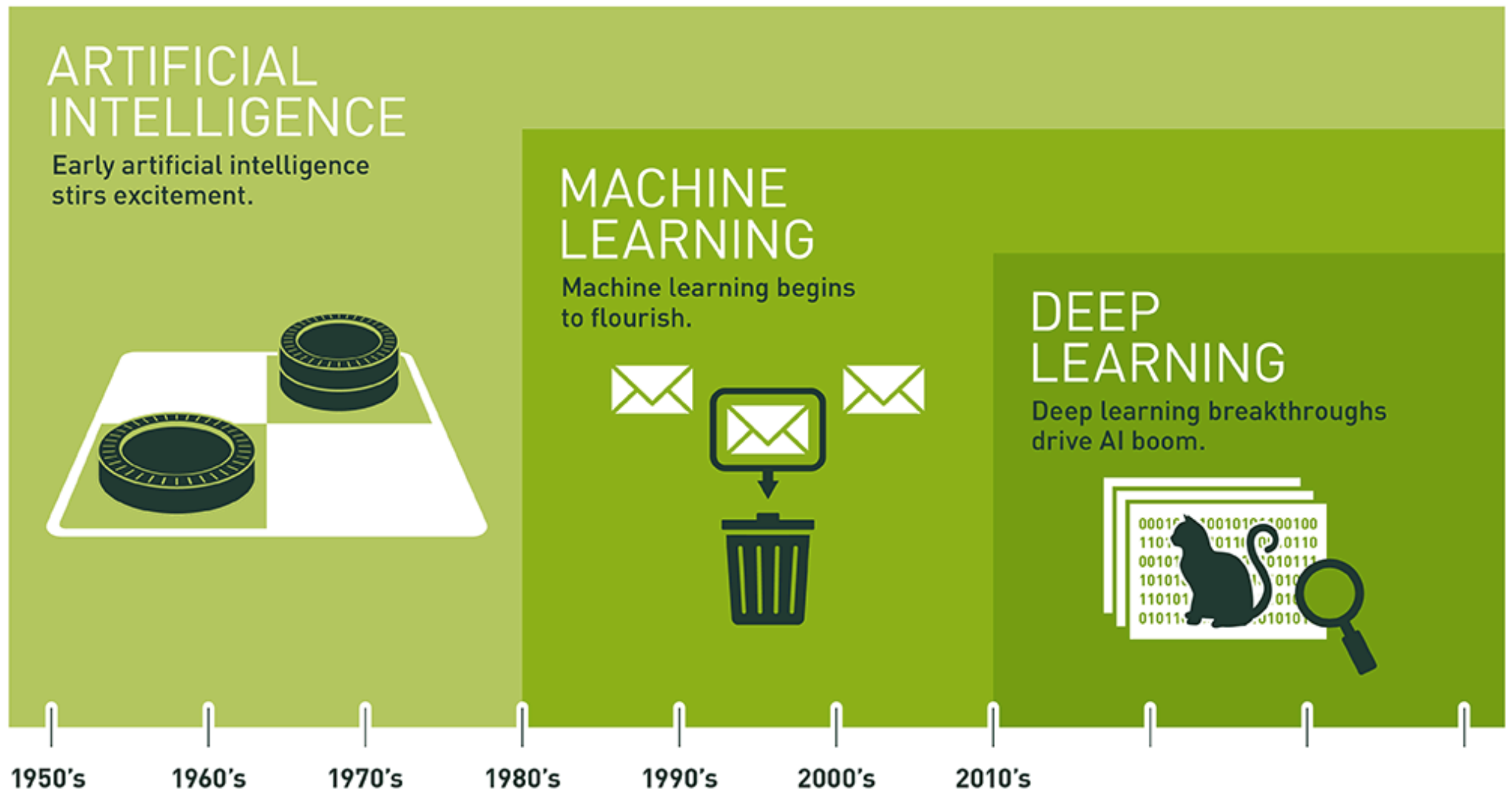
- Lens modeling is **very slow**.
- Even a simple lens model can take 2-3 days of human and CPU time, translating to **1,400 years !!!**
- Even if we pay **100 people** to work on this, it'll be **14 years!!!** Old method are simply not feasible.



Lens modeling sweatshop of 2022



# Can AI (deep learning) helps?



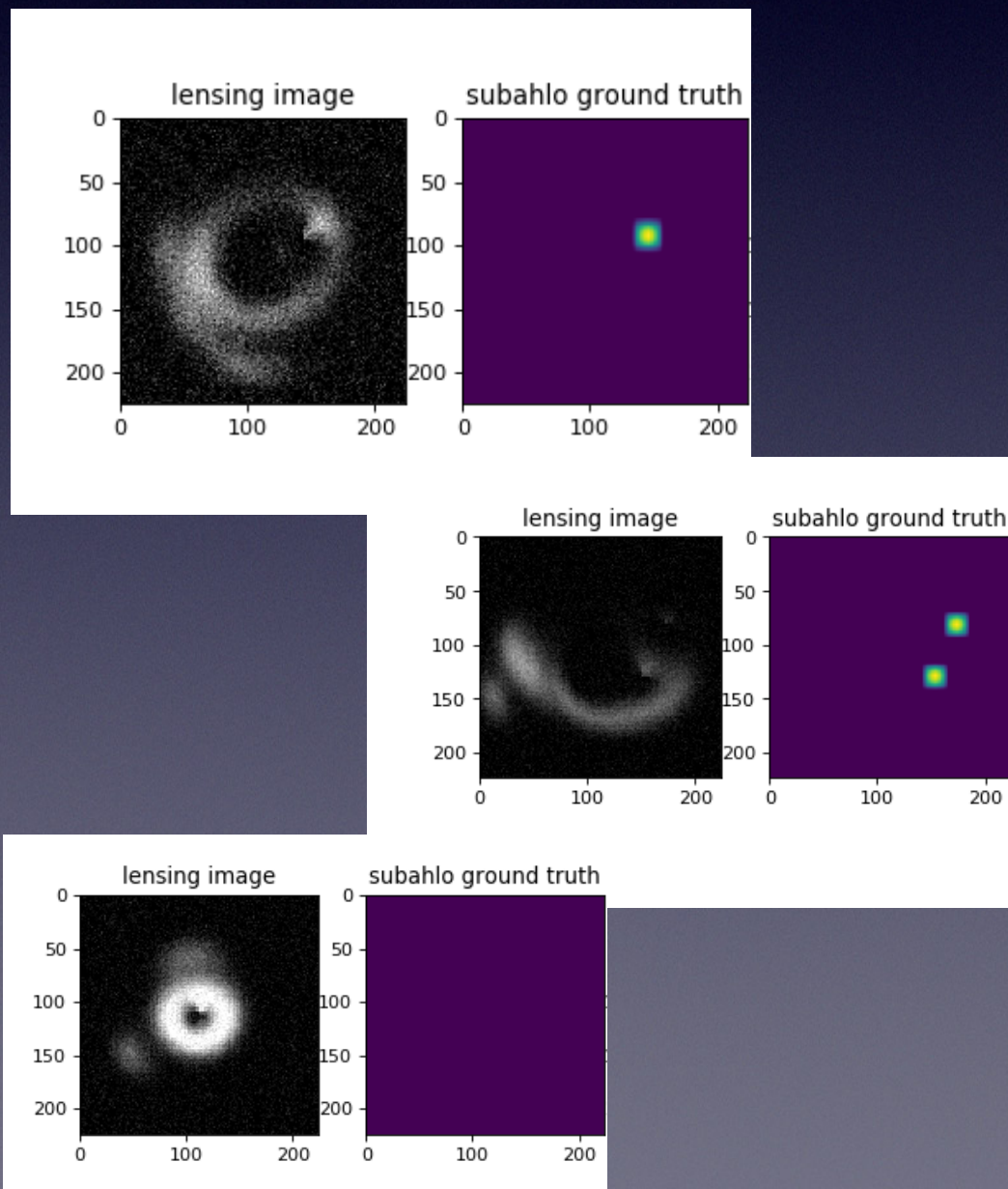
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Image credit: Nvidia



# Deep learning setup

20000 simulated data as training set

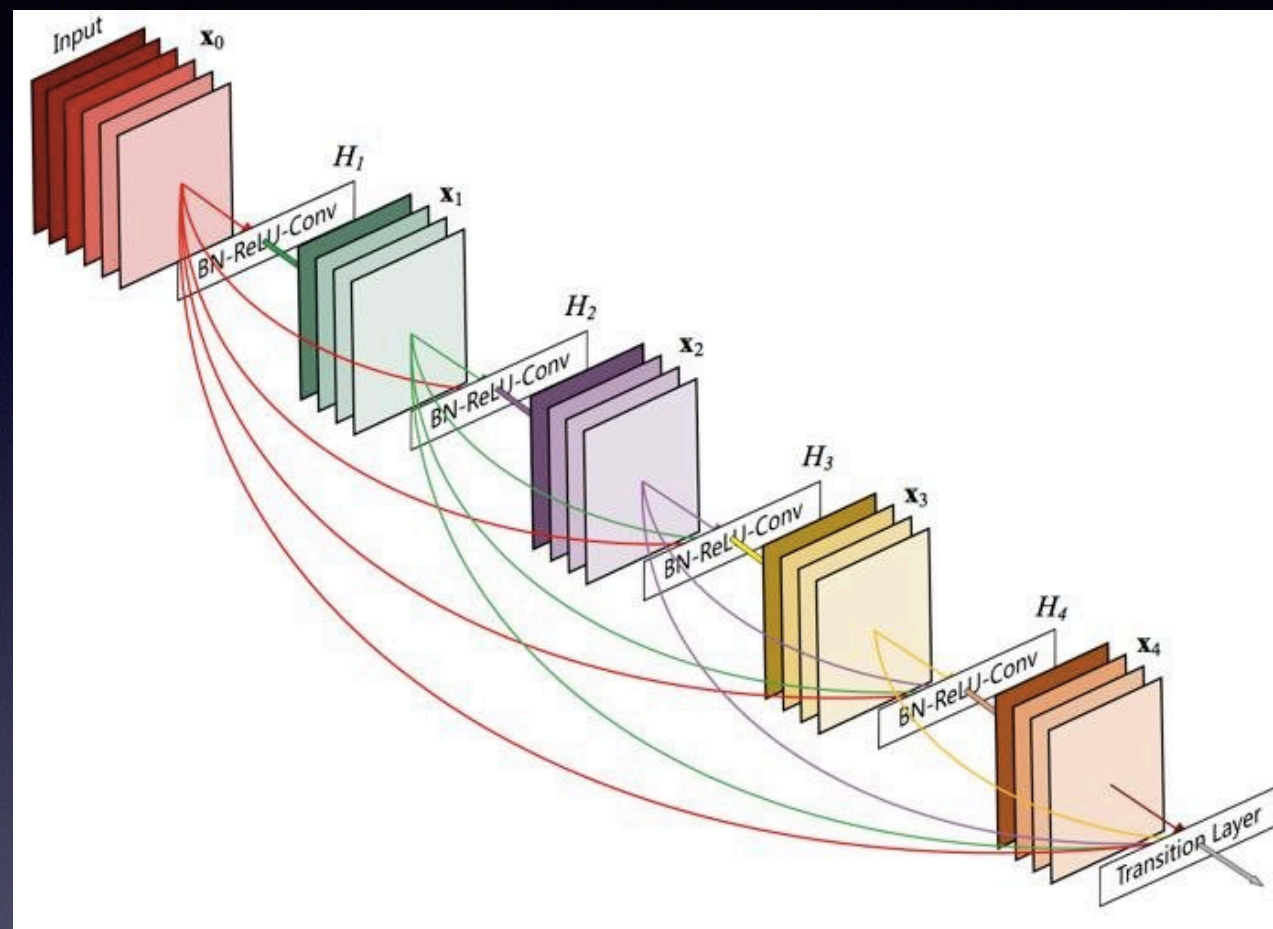


- 20000 simulated data [images and subhalo ground truth] as training set
- 2000 “DIFFERENT” data [images] as test set
- Simulation with SIE (marco lens) contains 0-5 subhalos (perturbers)
- Loss function: Binary Cross Entropy with Logits Loss (of subhalo probability map)
- Adam Optimizer, learning rate =  $1e-4$
- NN model: DenseNet 121
- Nvidia GPU: 1080Ti

**PYTORCH**

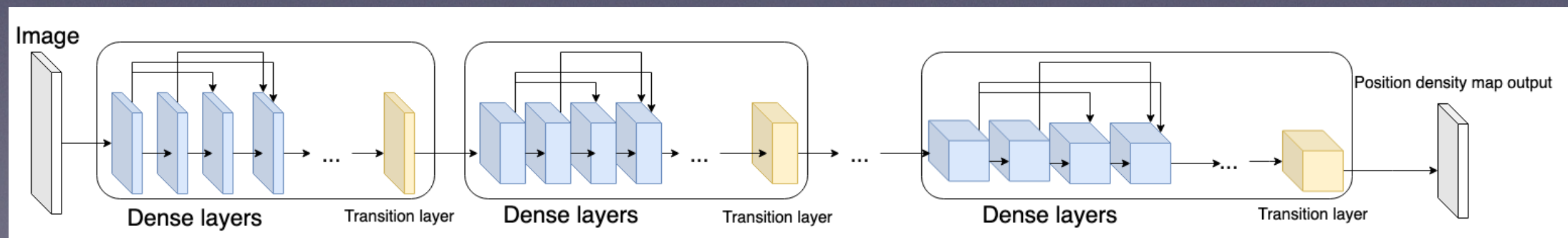


# DenseNet



DenseNet architecture (121 layers)

Gao Huang et al., ArXiv:1608.06993



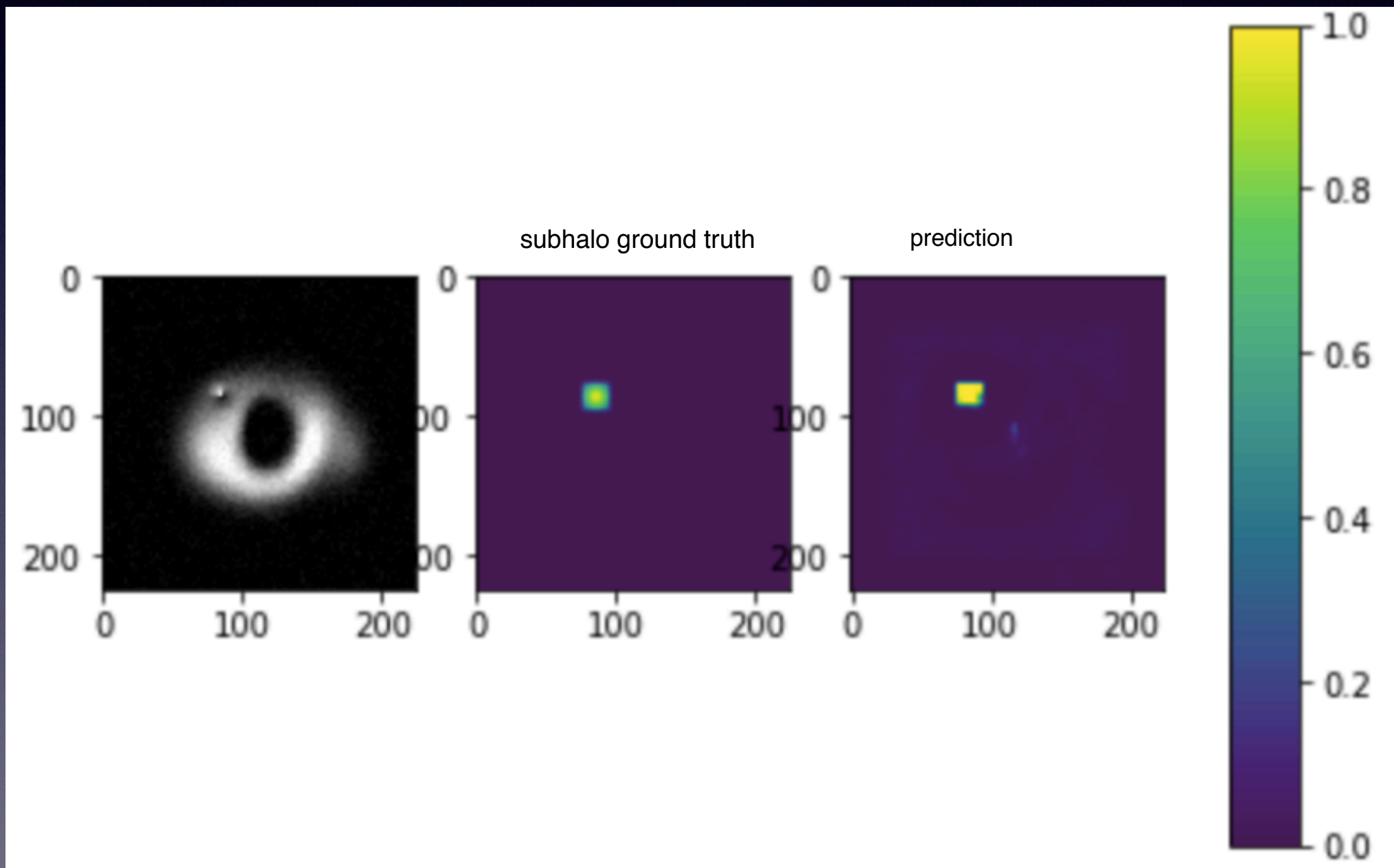


# Let's check how NN is doing



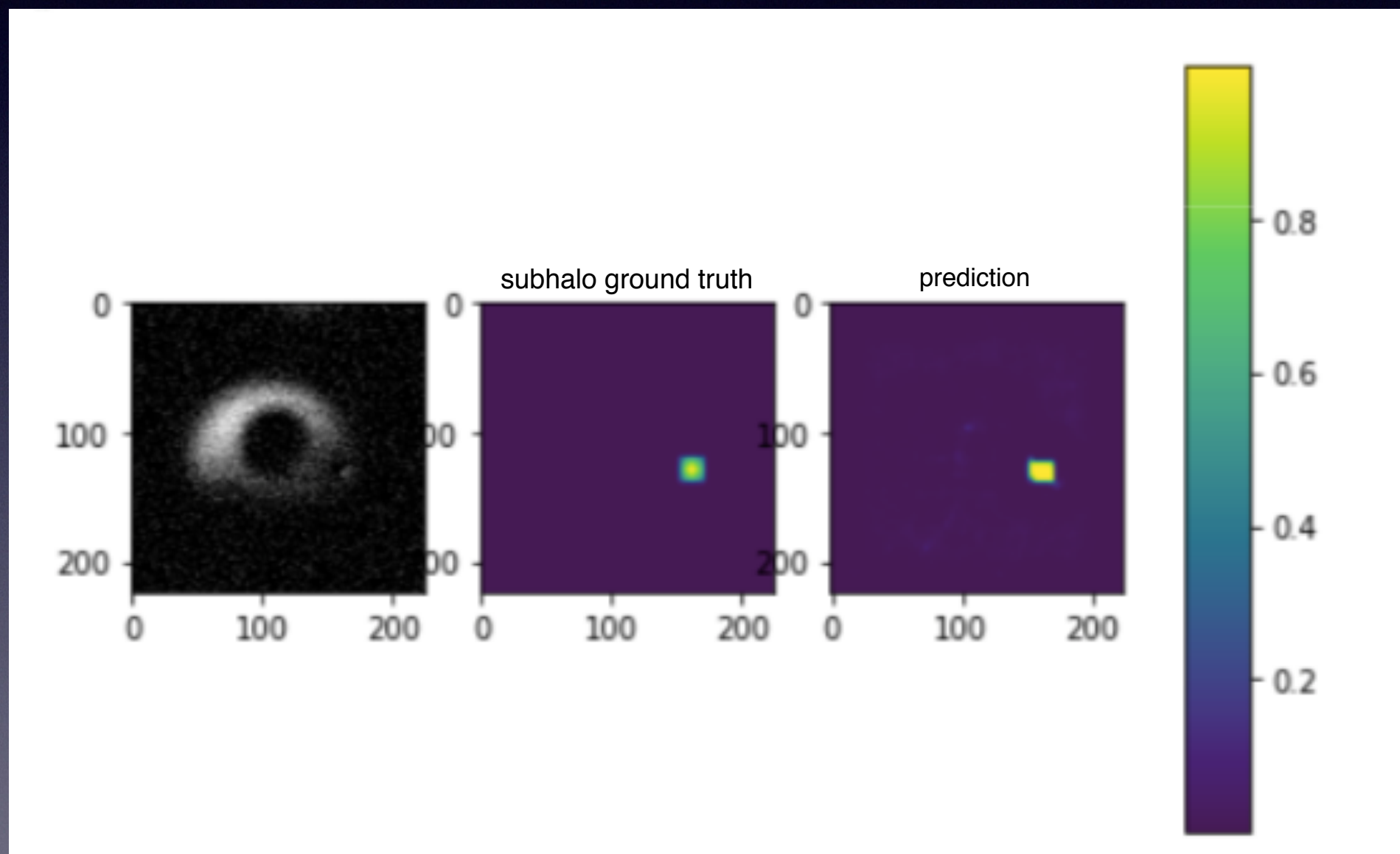


# Prediction: subhalo detected!



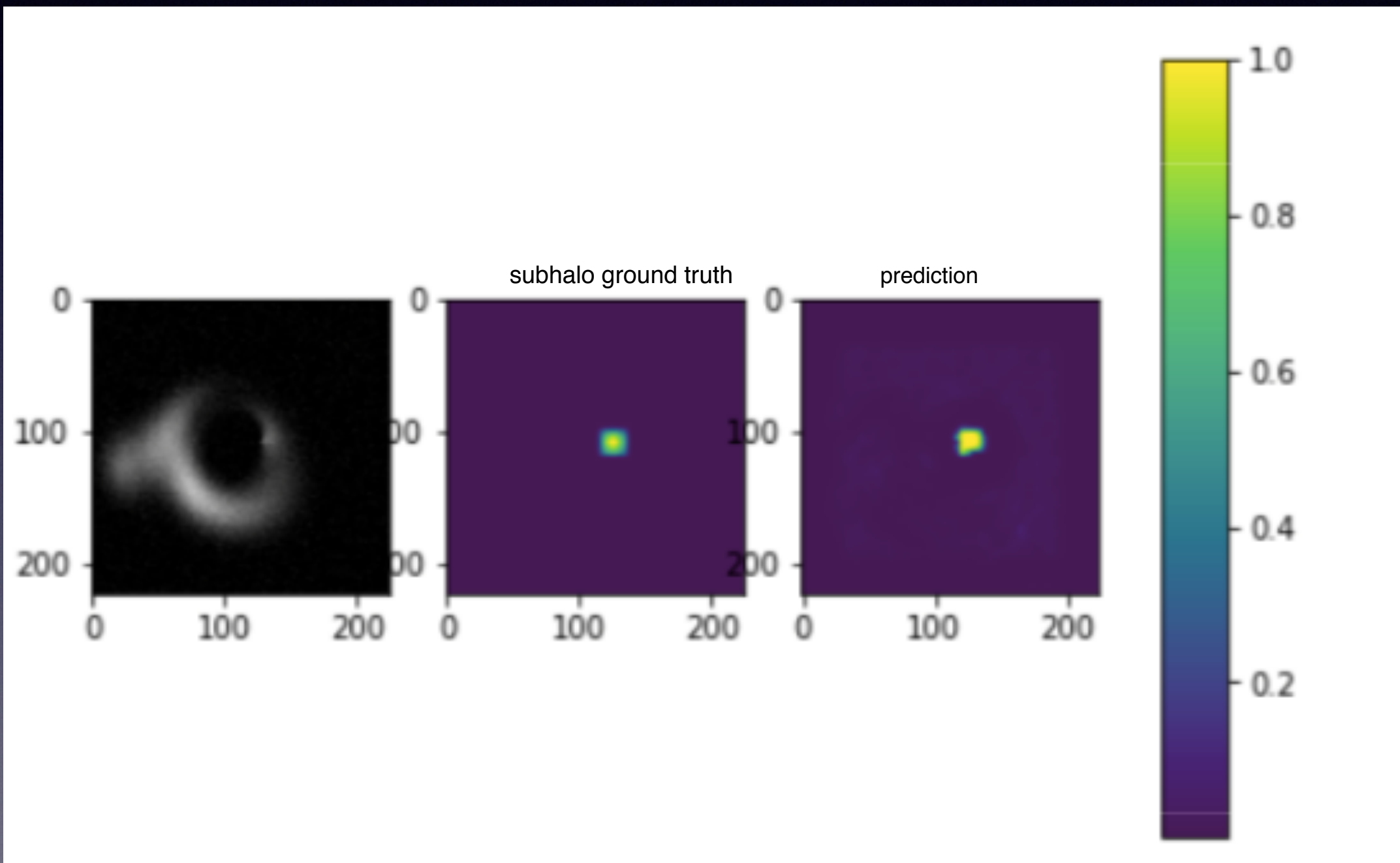


# Prediction: subhalo detected!



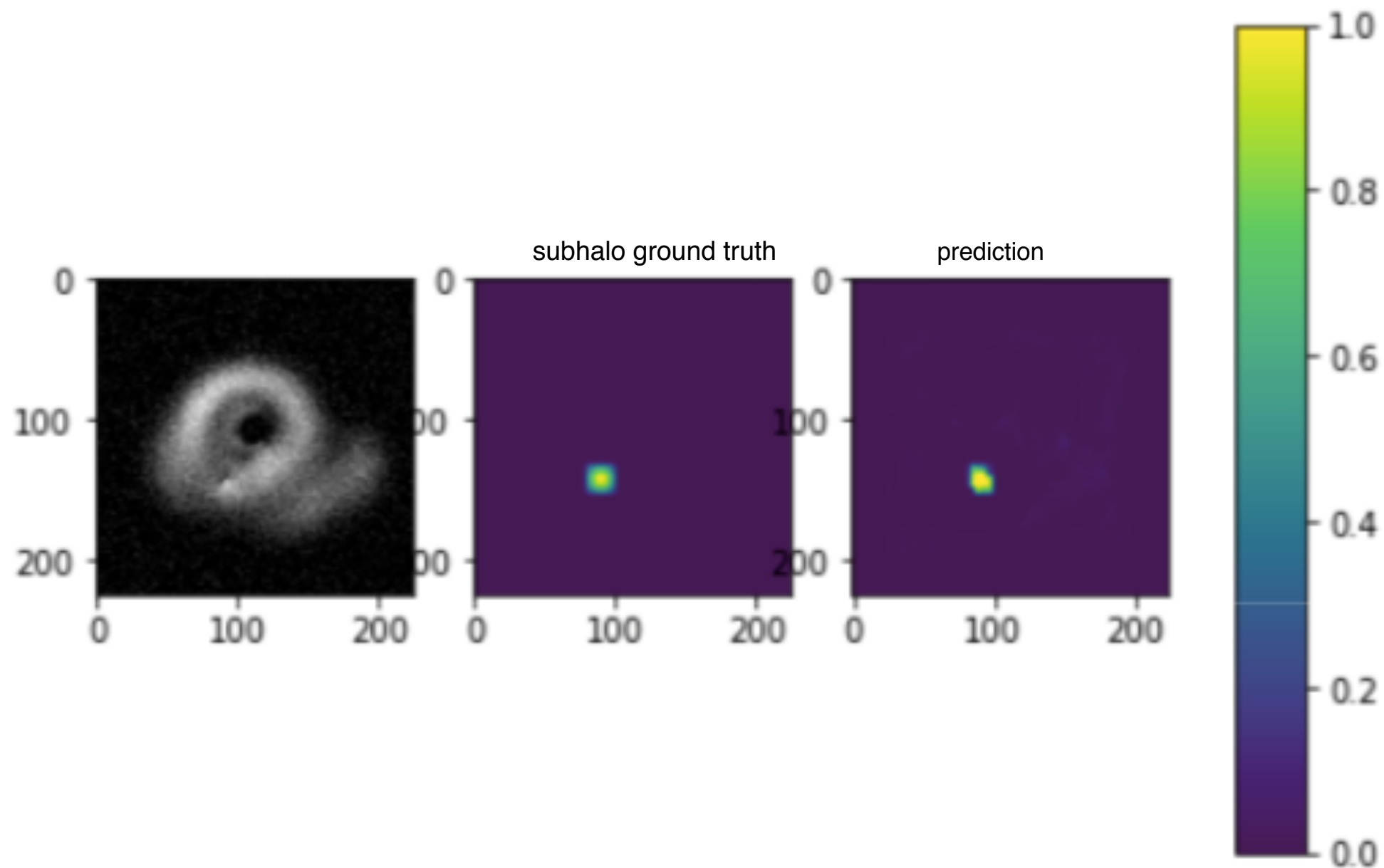


# Prediction: subhalo detected!



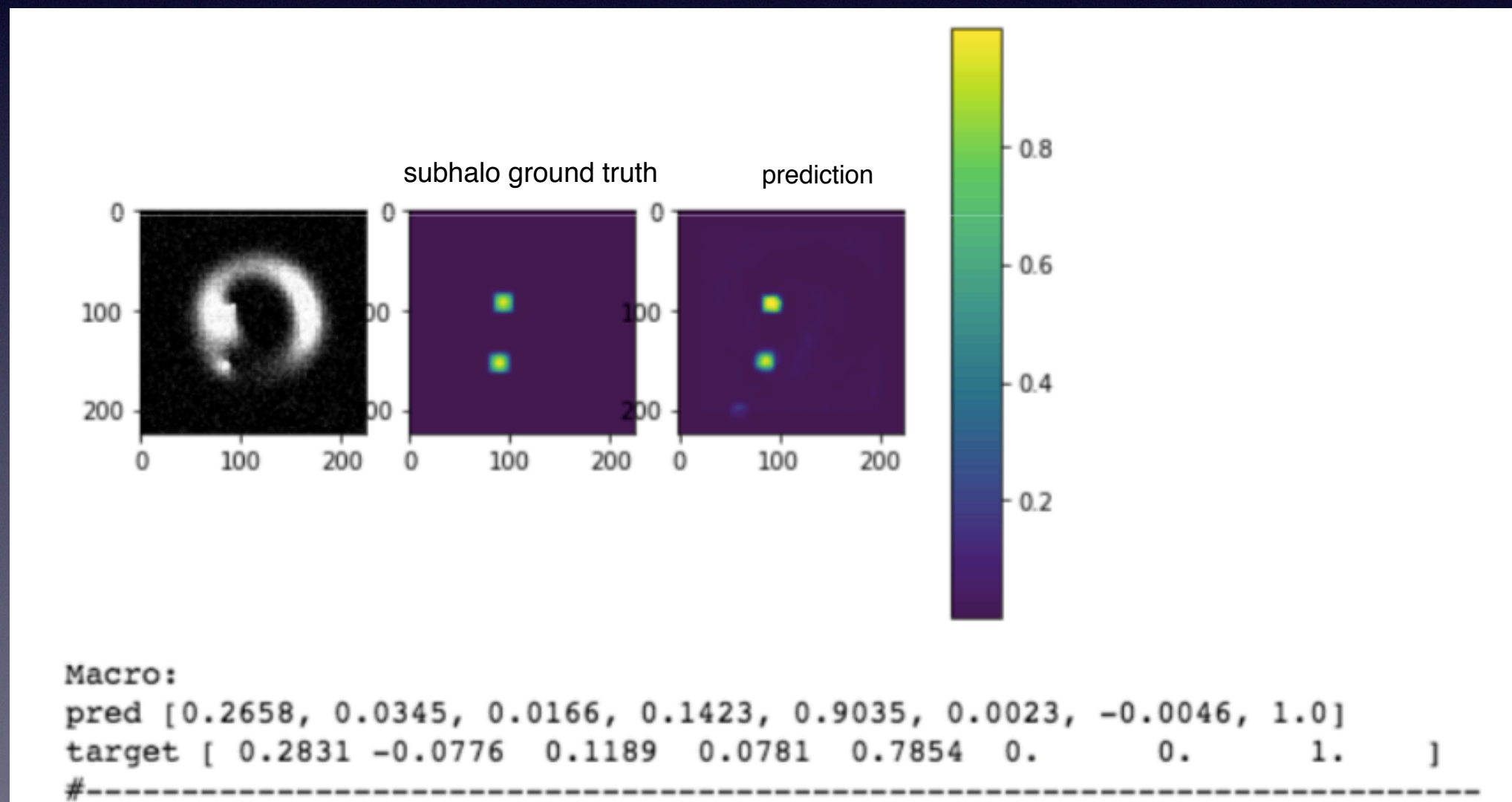


# Prediction: subhalo detected!



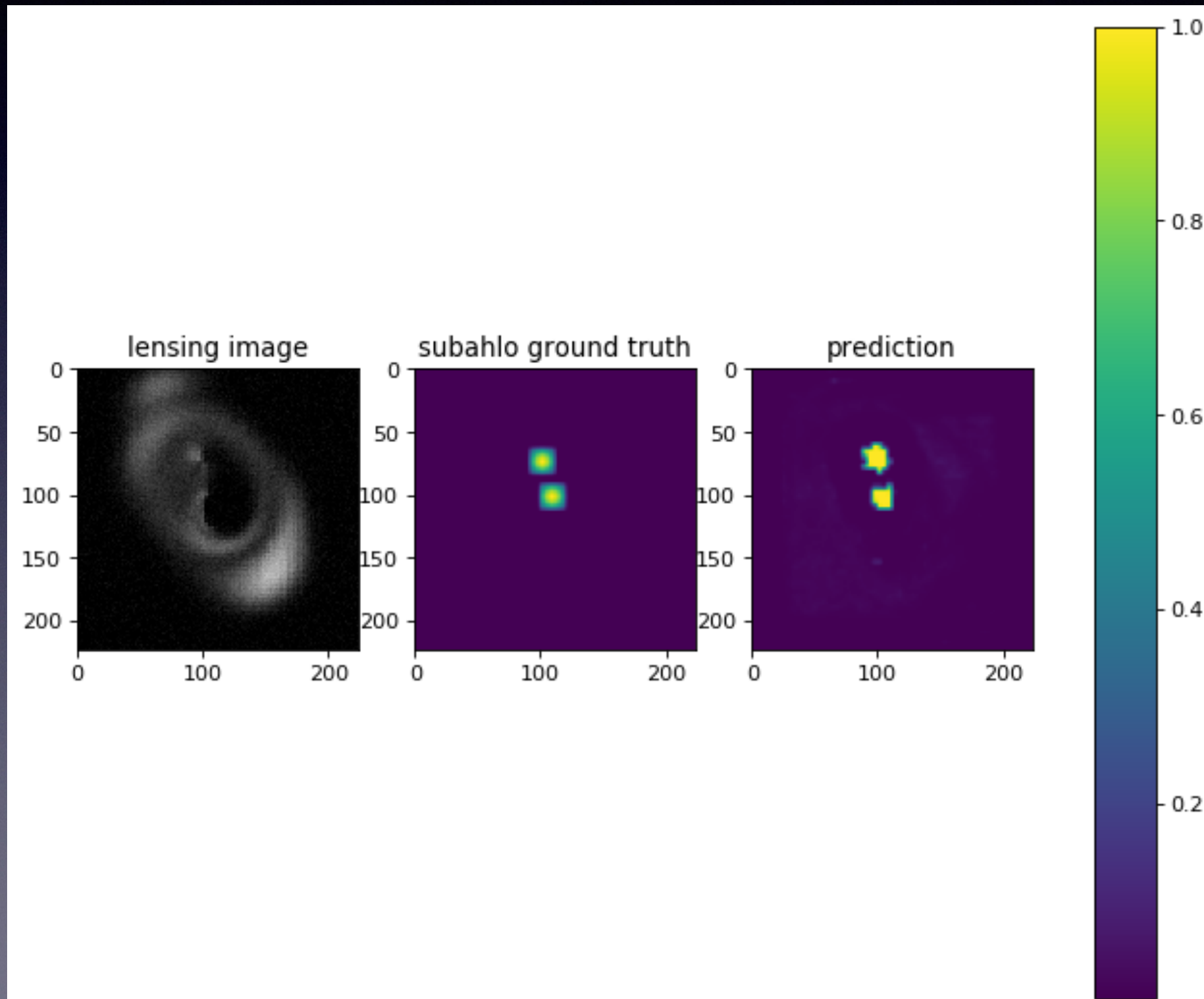


# Prediction: multiple subhalos!



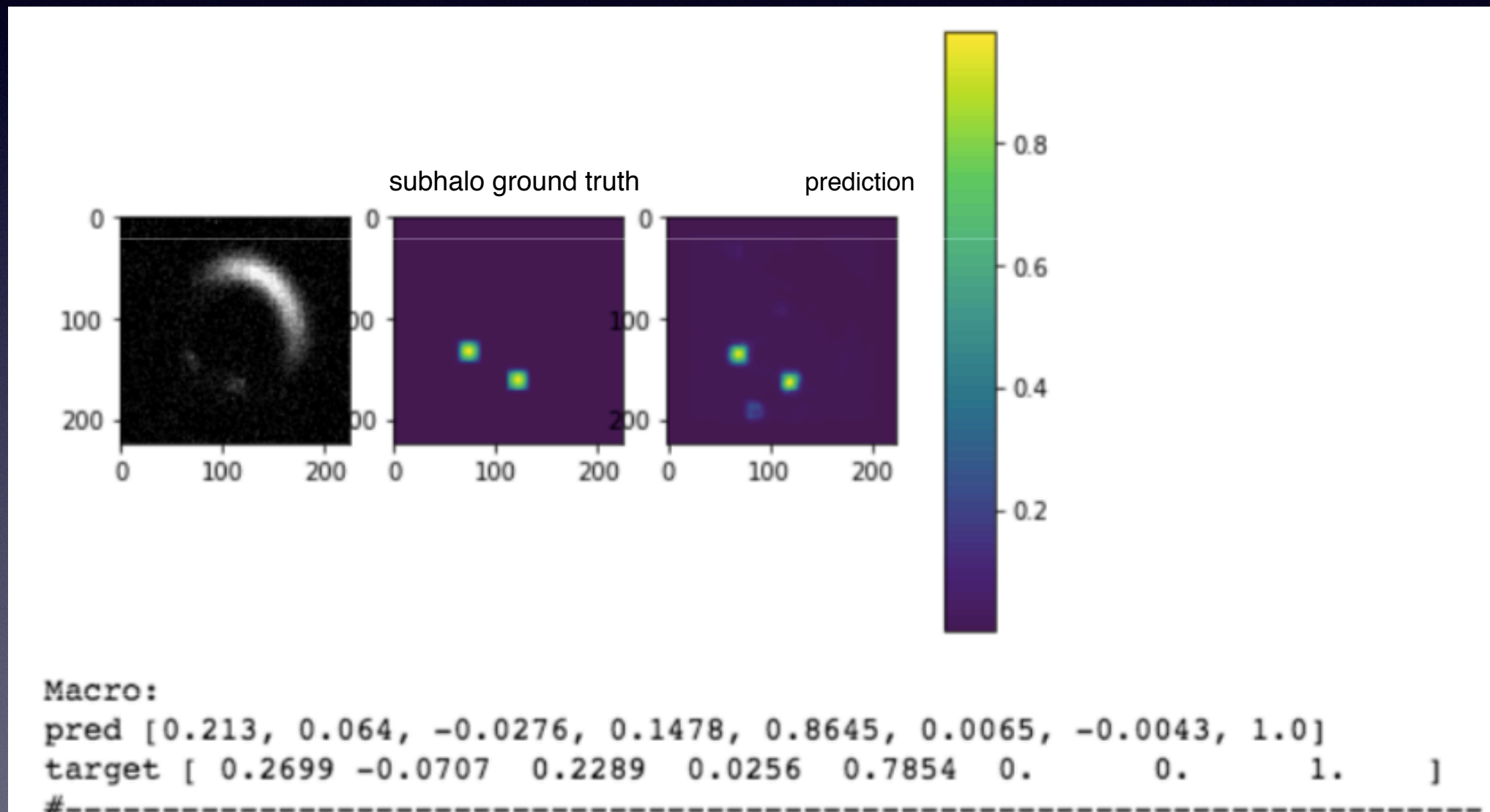


# Prediction: multiple subhalos!



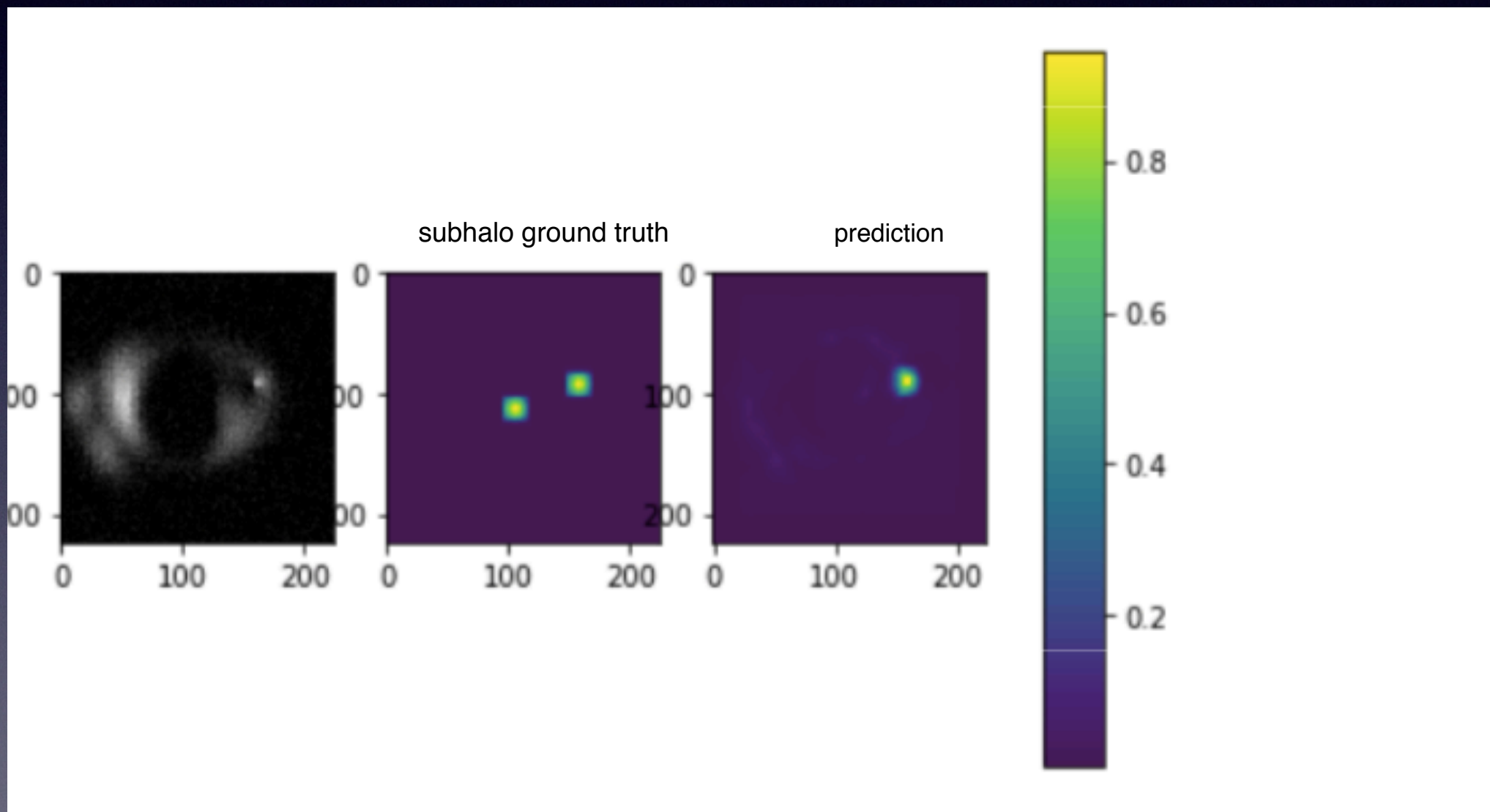


# Prediction: multiple subhalos!



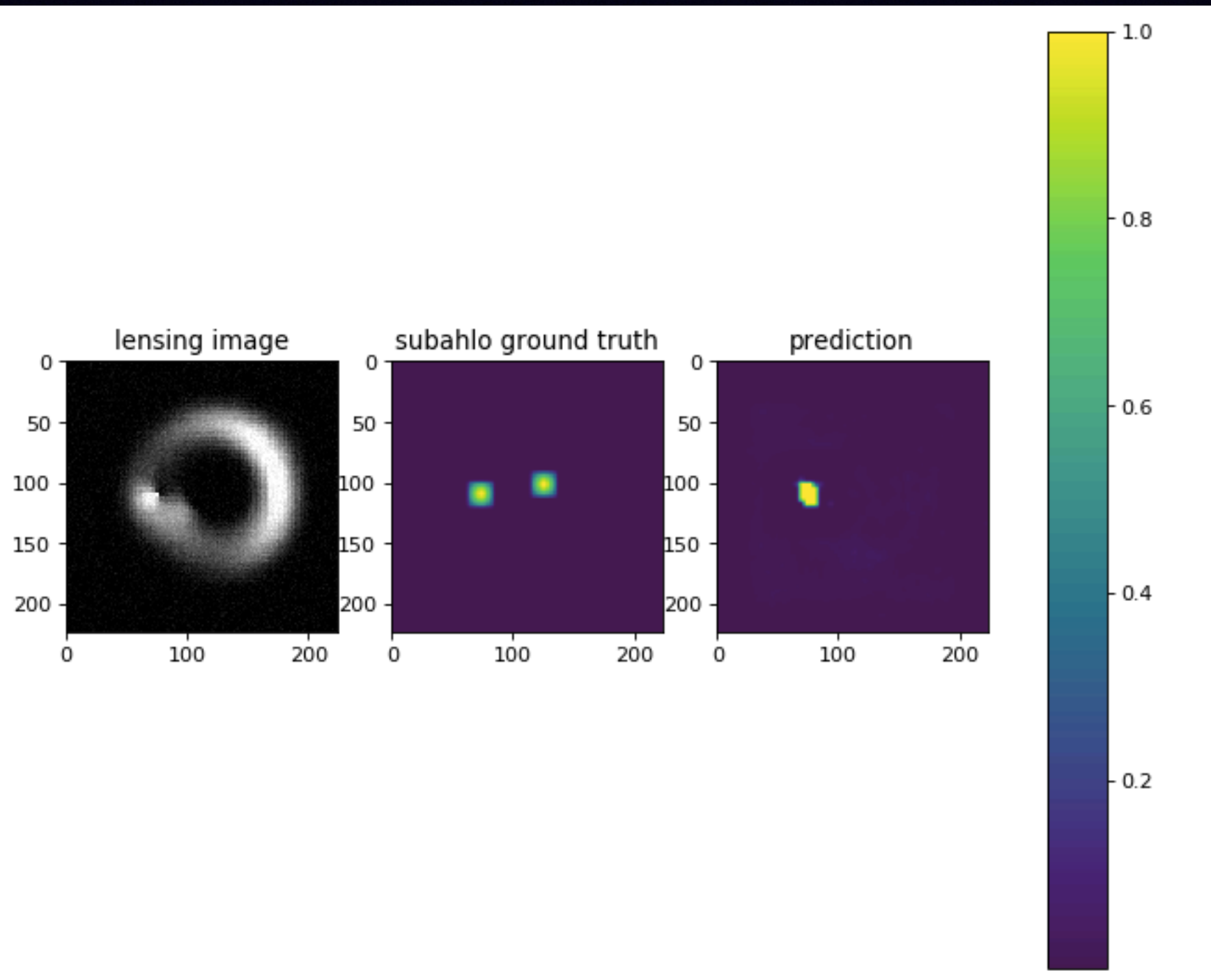


“Failed” good examples:  
Can’t see in the dark



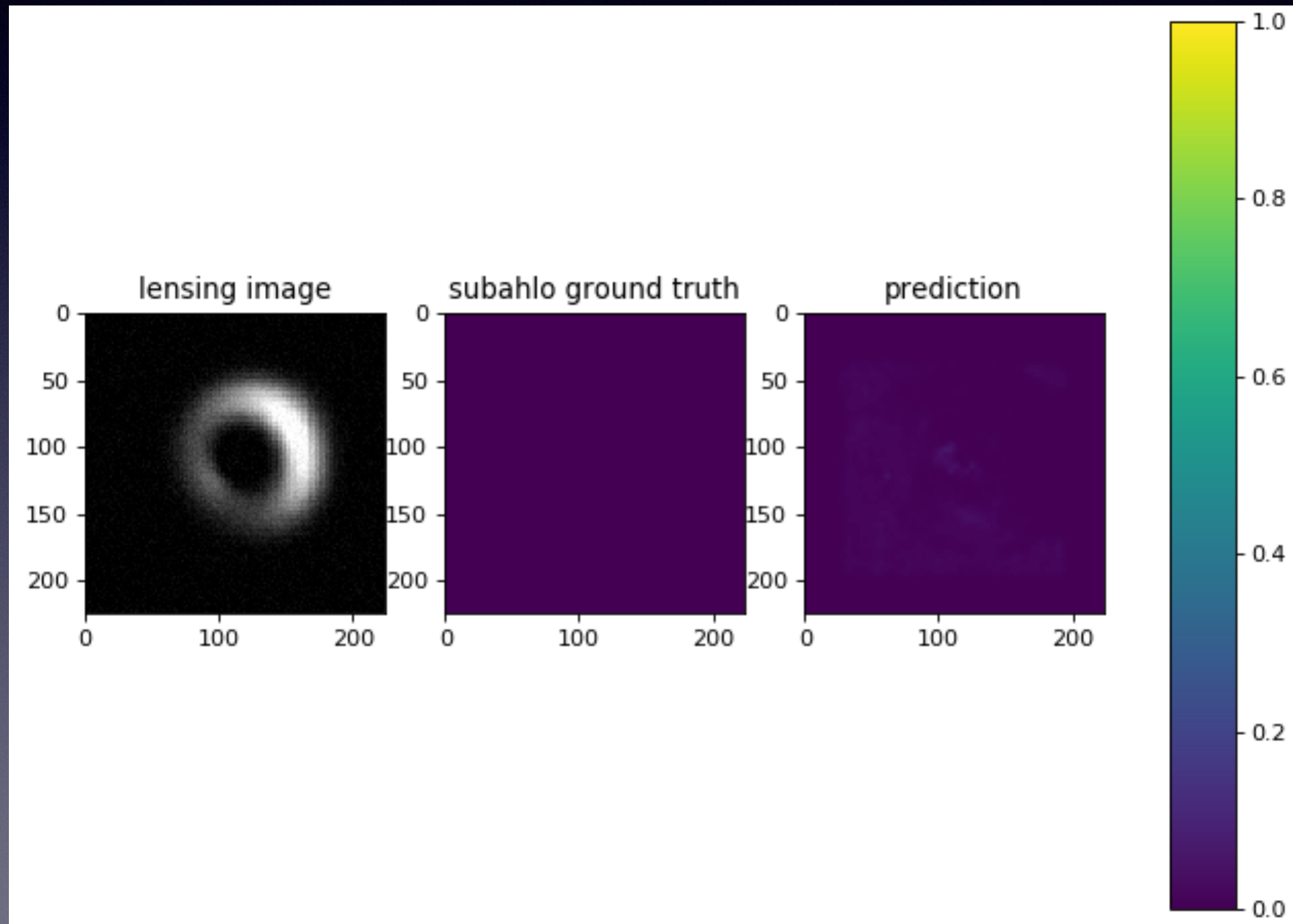


“Failed” good examples:  
Can't see in the dark



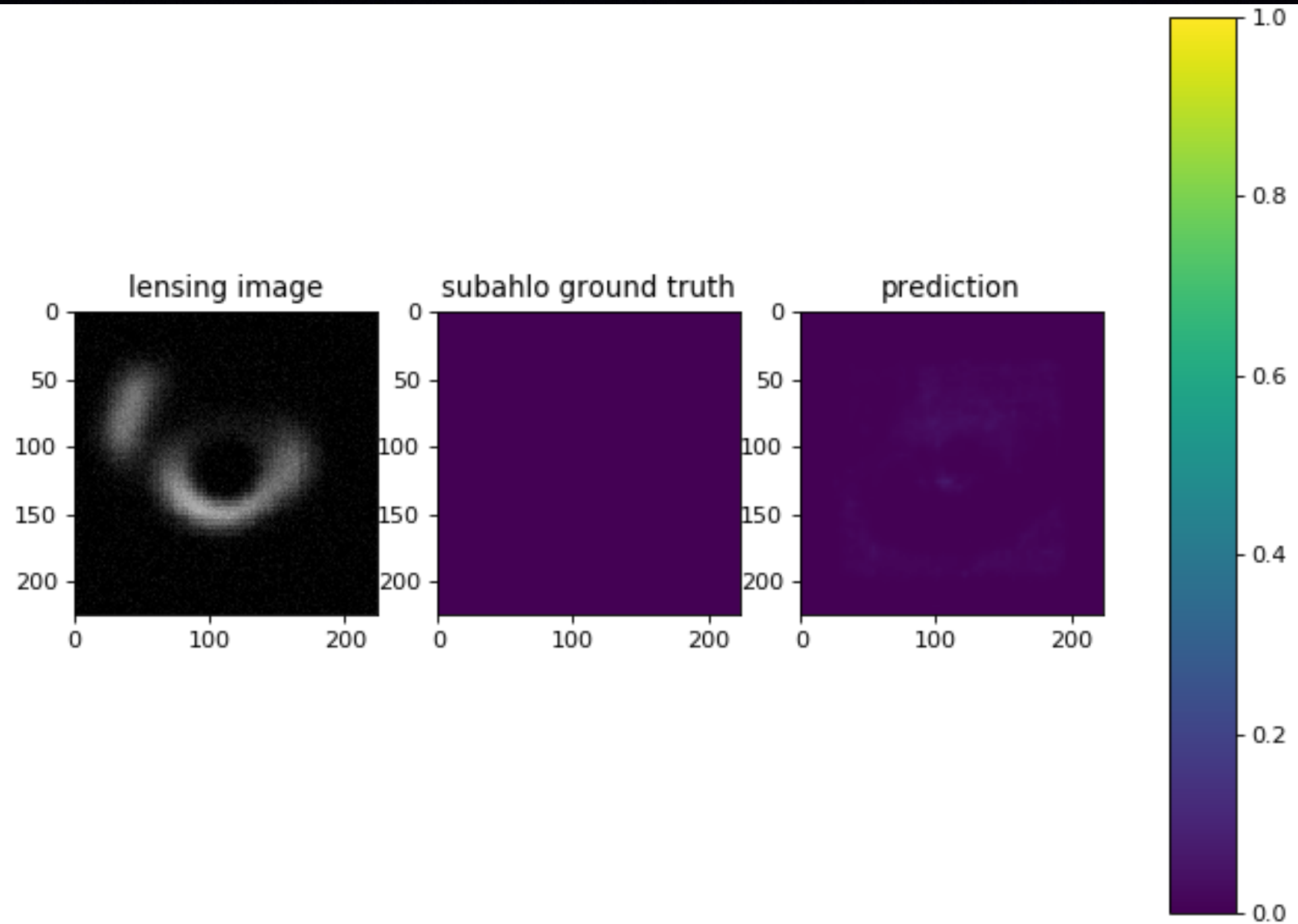


# Prediction: No subhalo



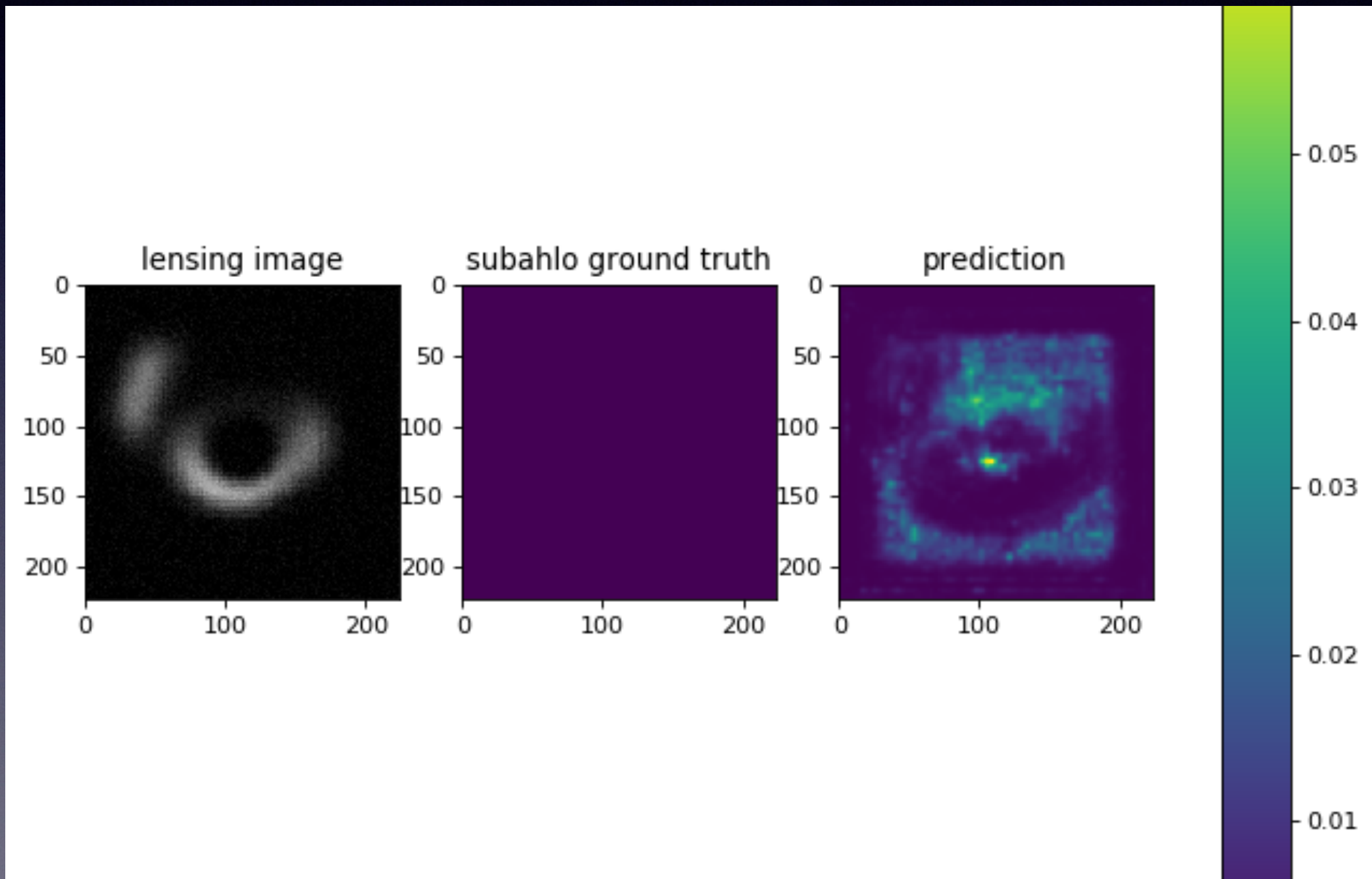


# Prediction: No subhalo



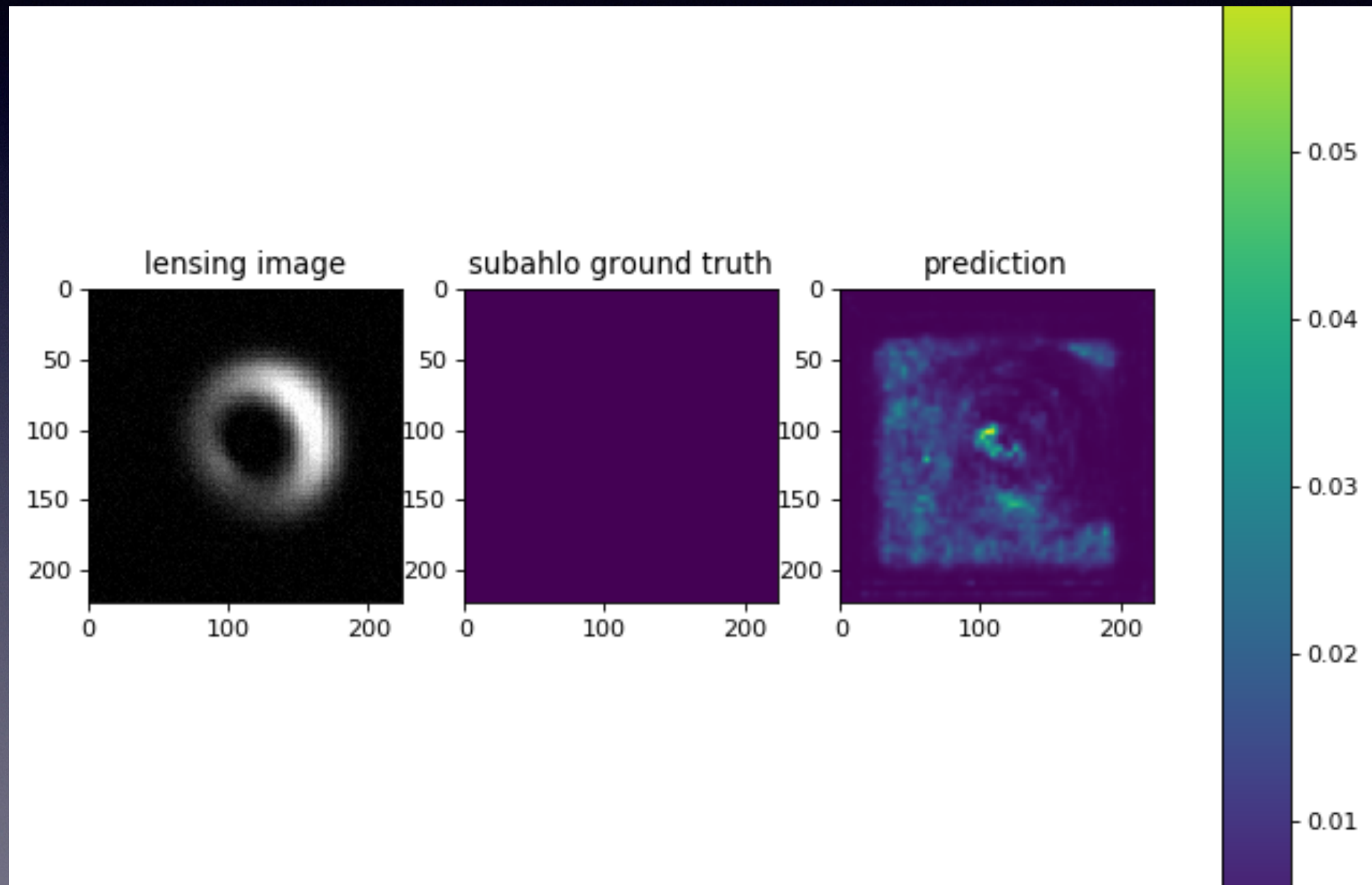


# “Rejection” of subhalo(s) around the arc



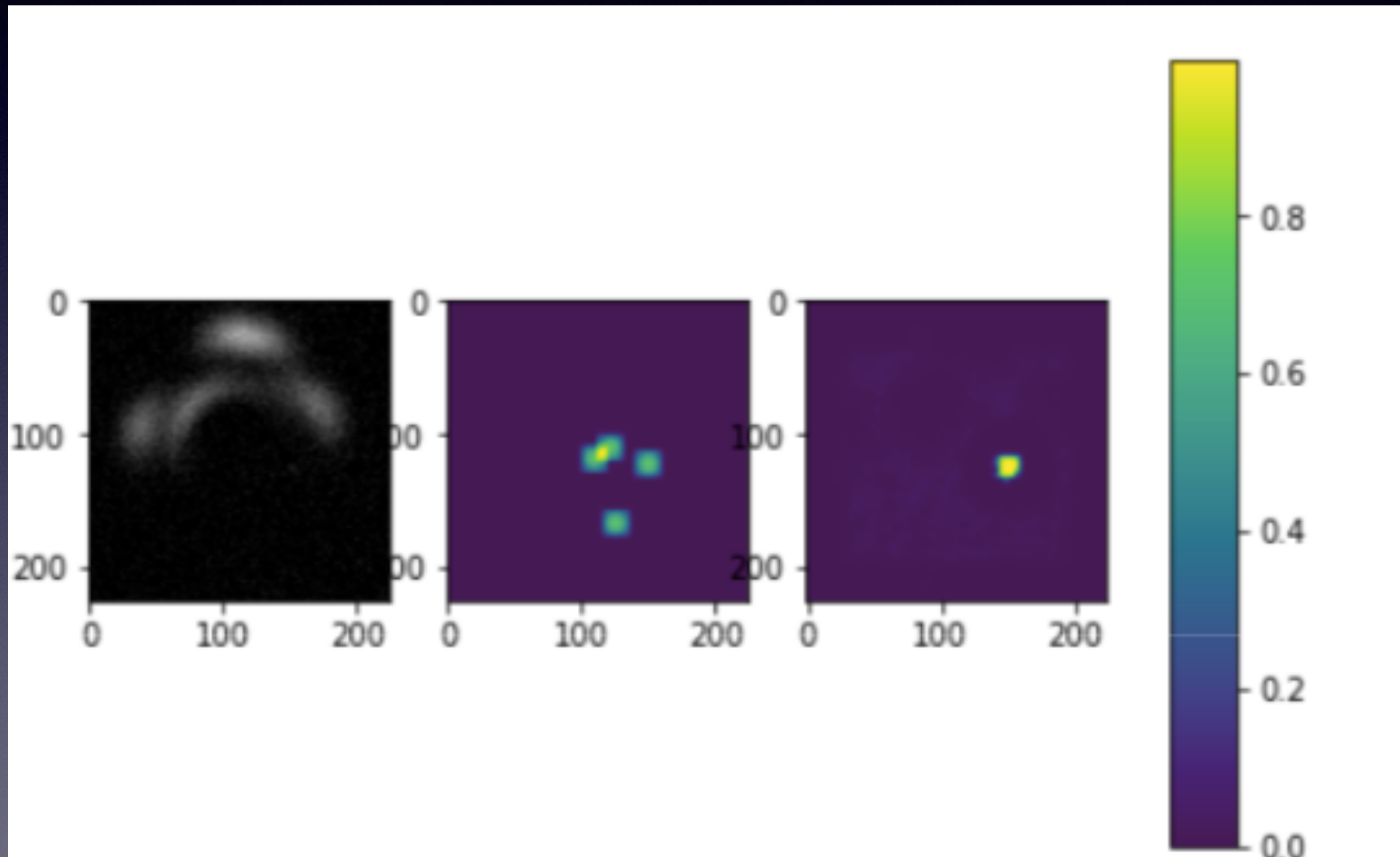


# “Rejection” of subhalo(s) around the arc



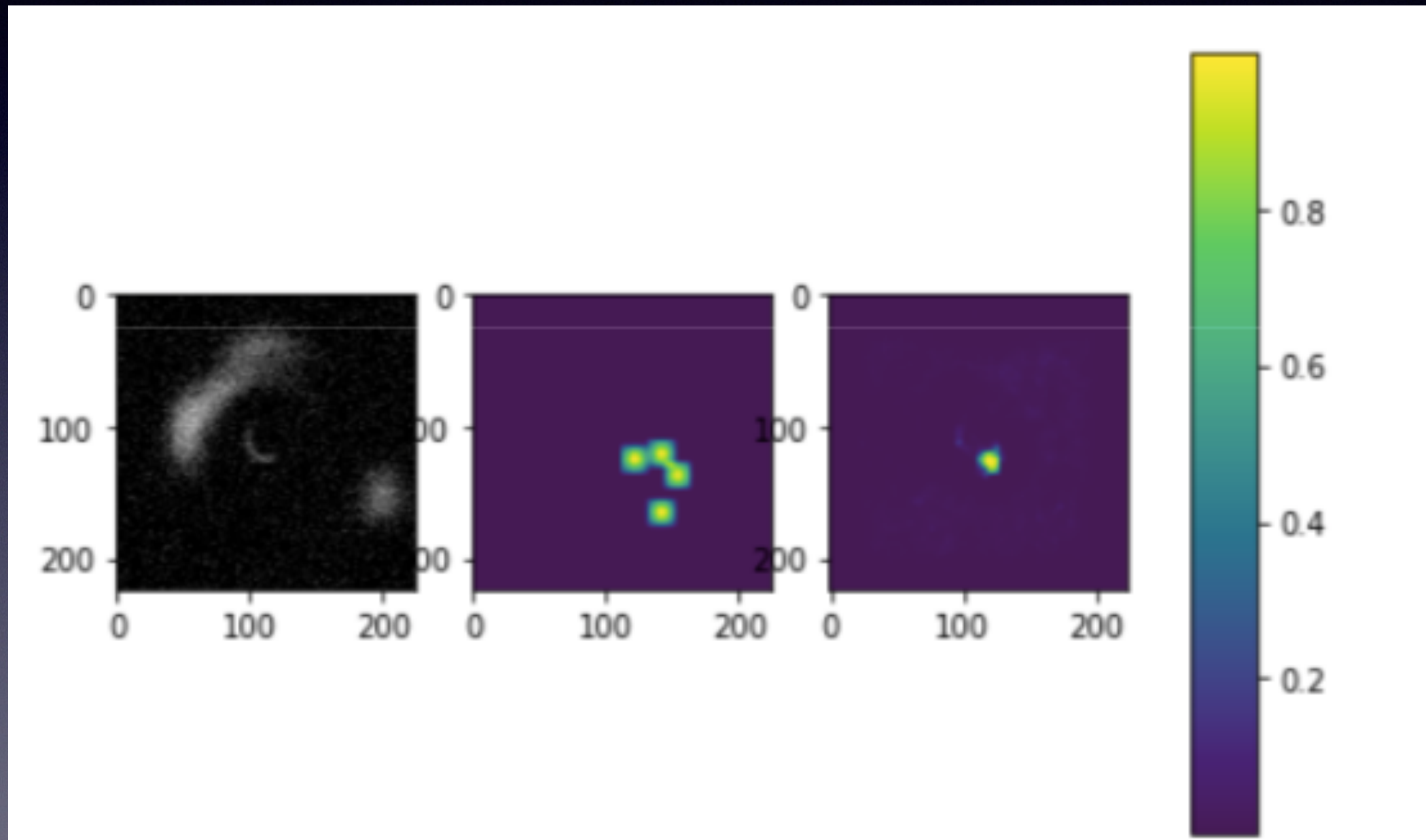


“Failed” prediction:  
Are they learning center of the mass?



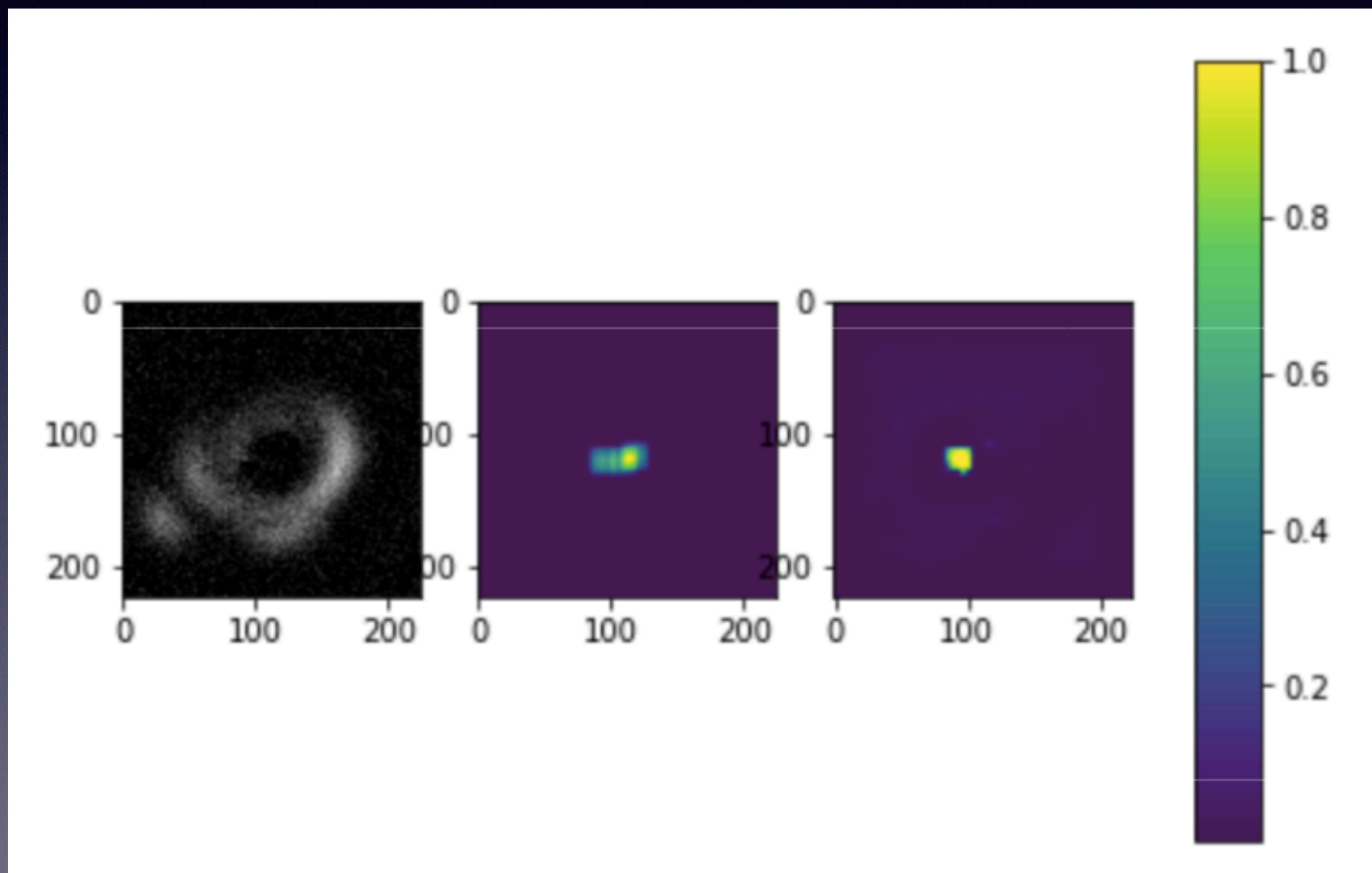


“Failed” prediction:  
Are they learning center of the mass?





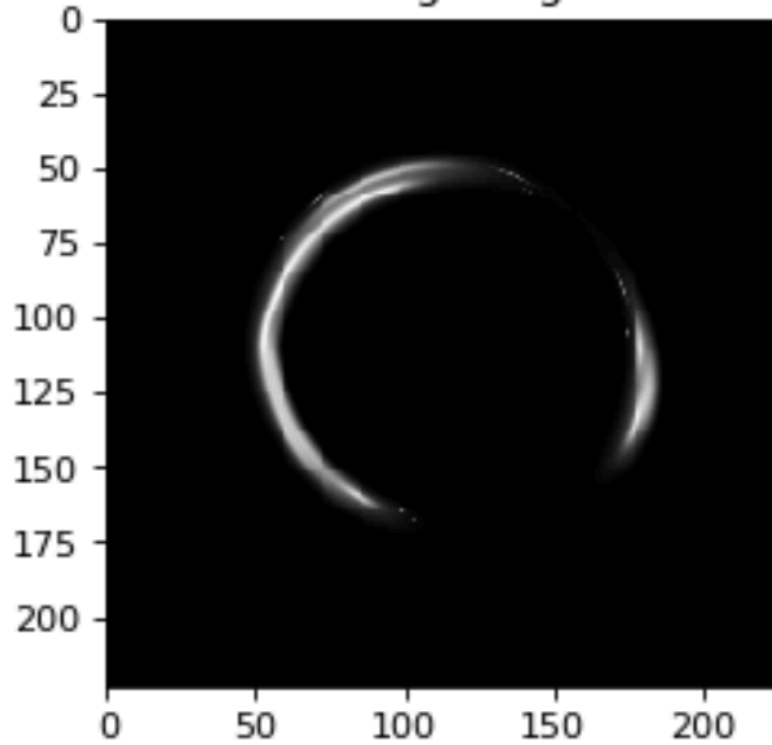
“Failed” prediction:  
Are they learning center of the mass?



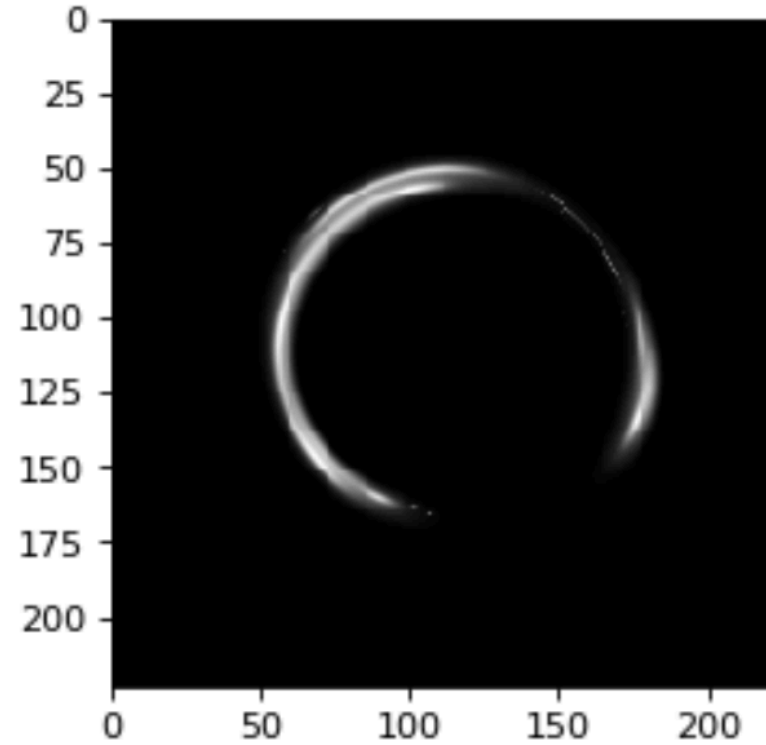


# Realistic simulation

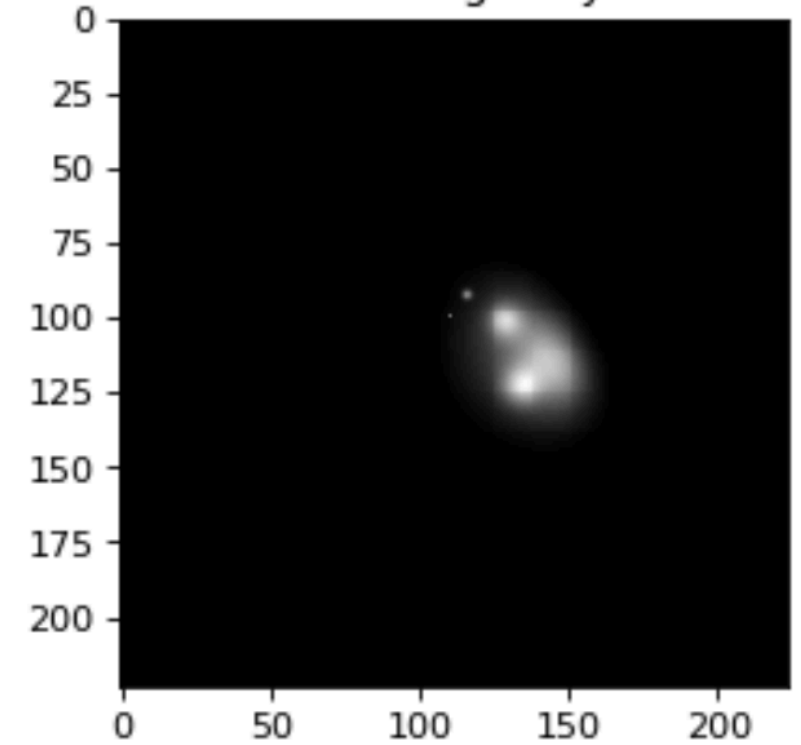
lensing image



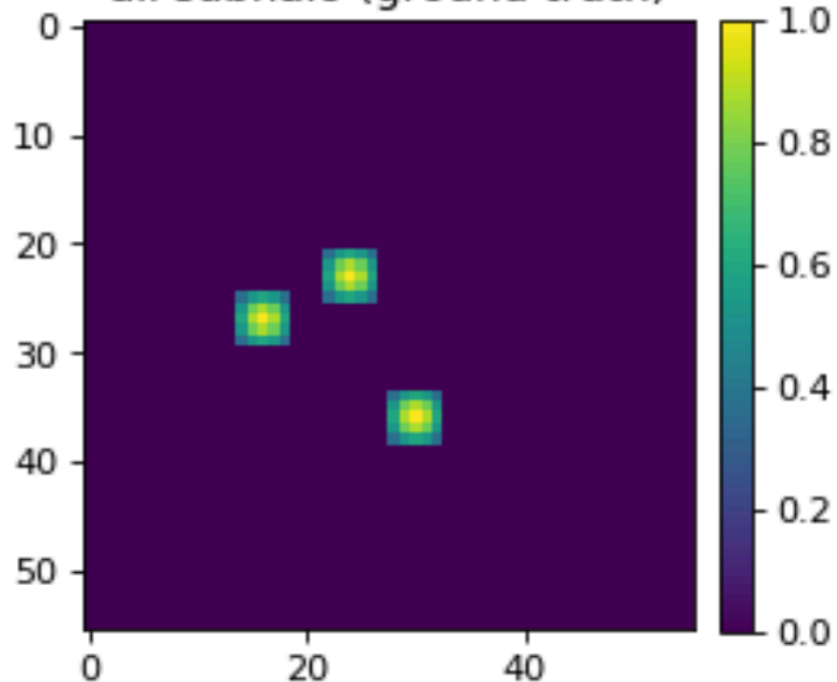
smooth model



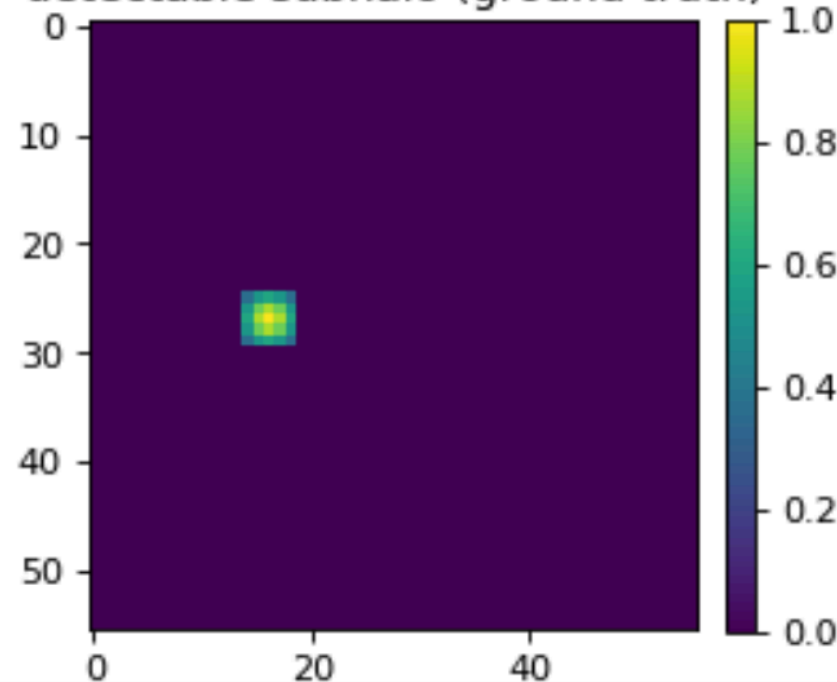
source galaxy



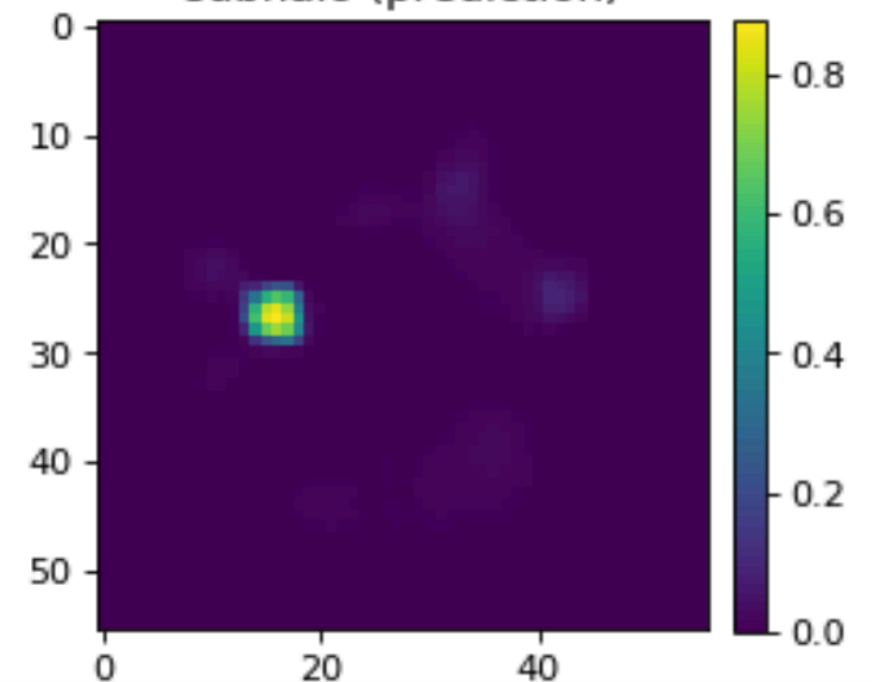
all subhalo (ground truth)



detectable subhalo (ground truth)

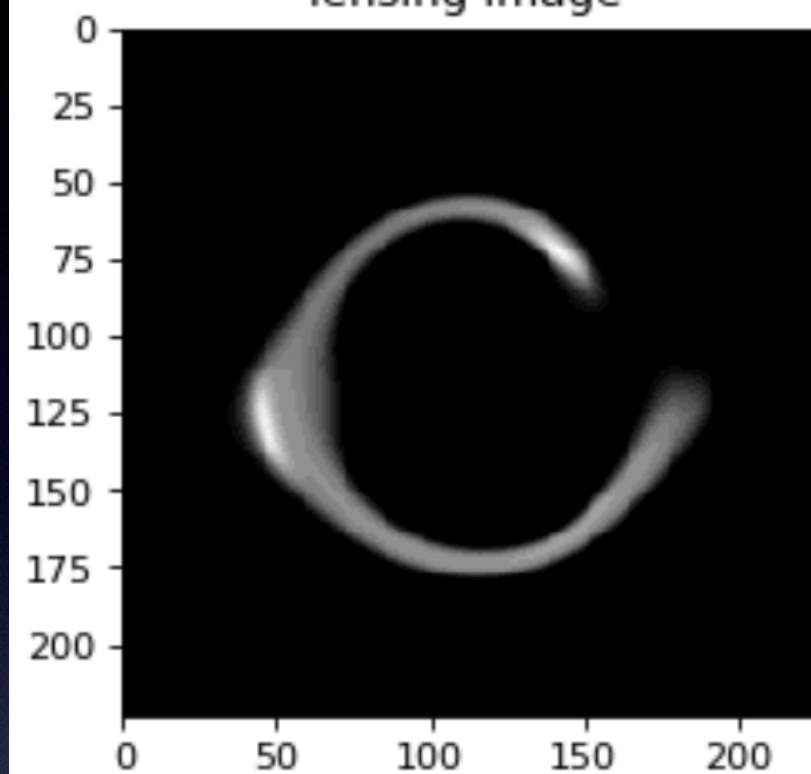


subhalo (prediction)

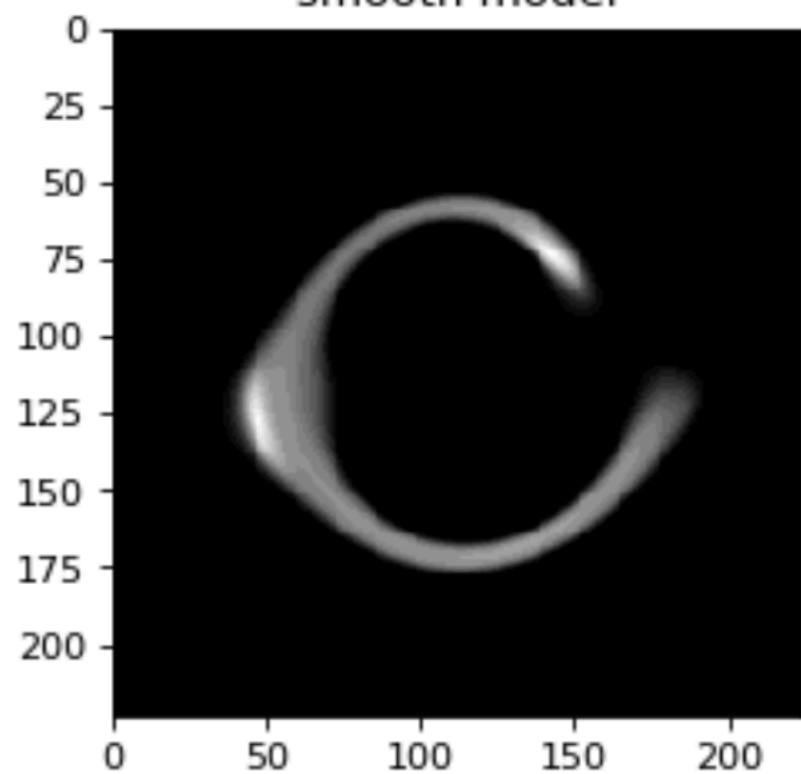




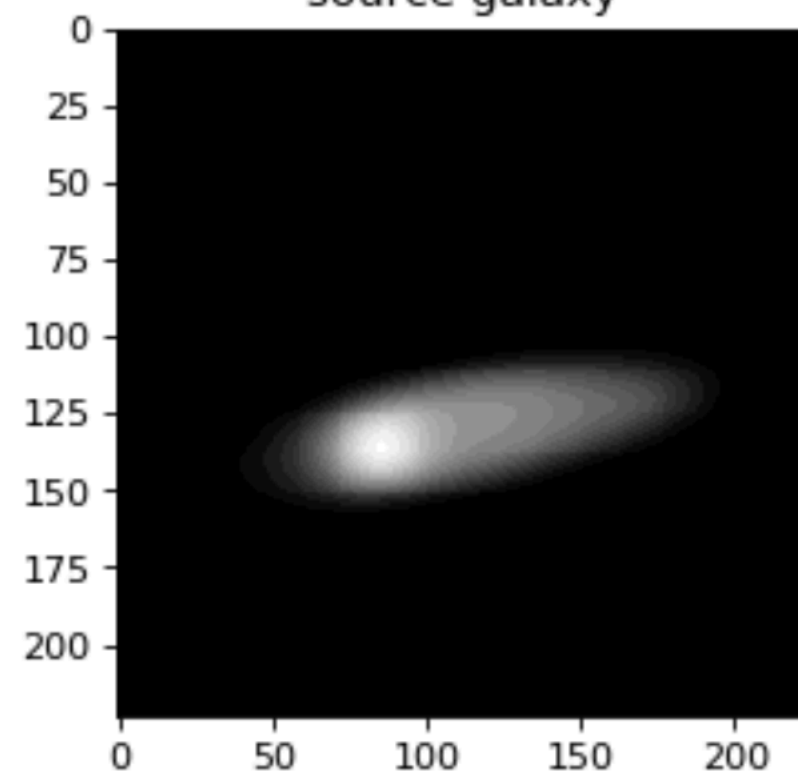
lensing image



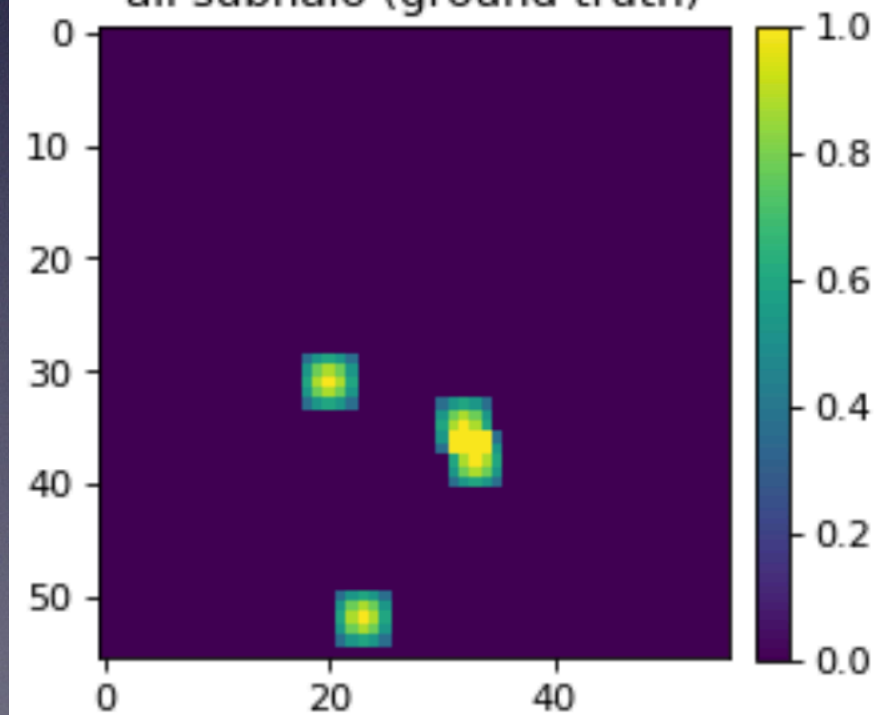
smooth model



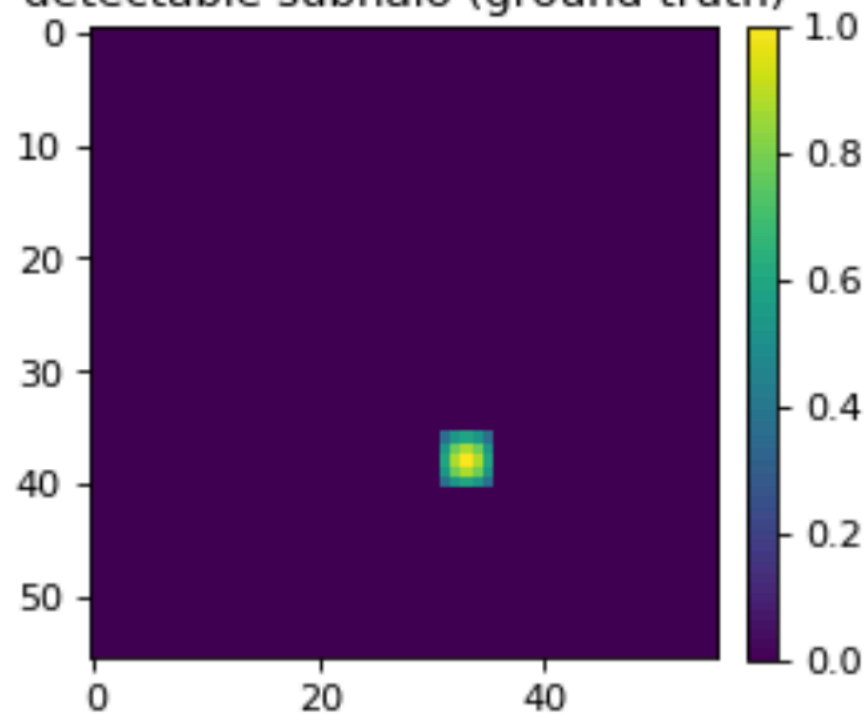
source galaxy



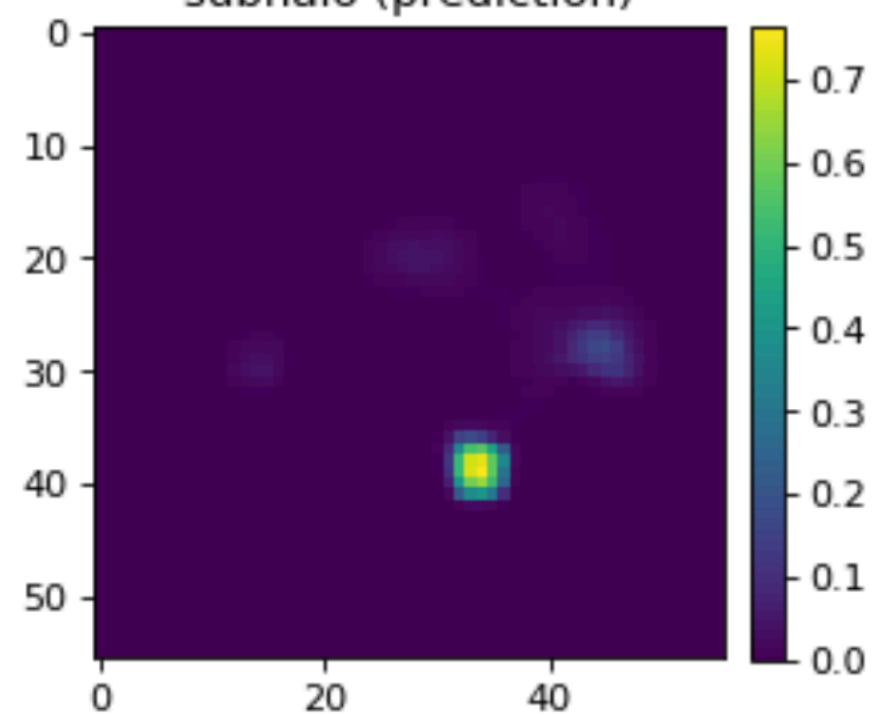
all subhalo (ground truth)



detectable subhalo (ground truth)

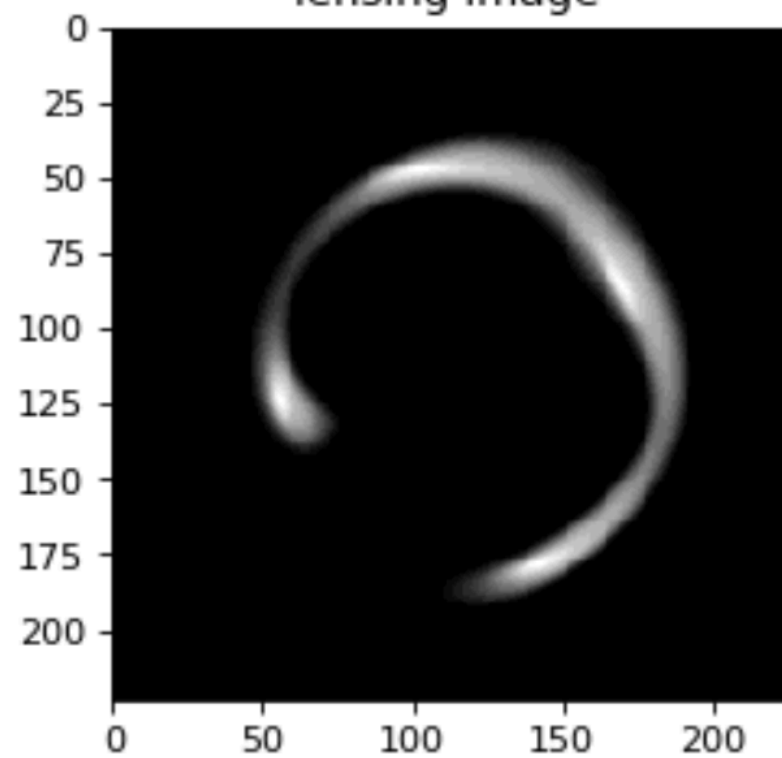


subhalo (prediction)

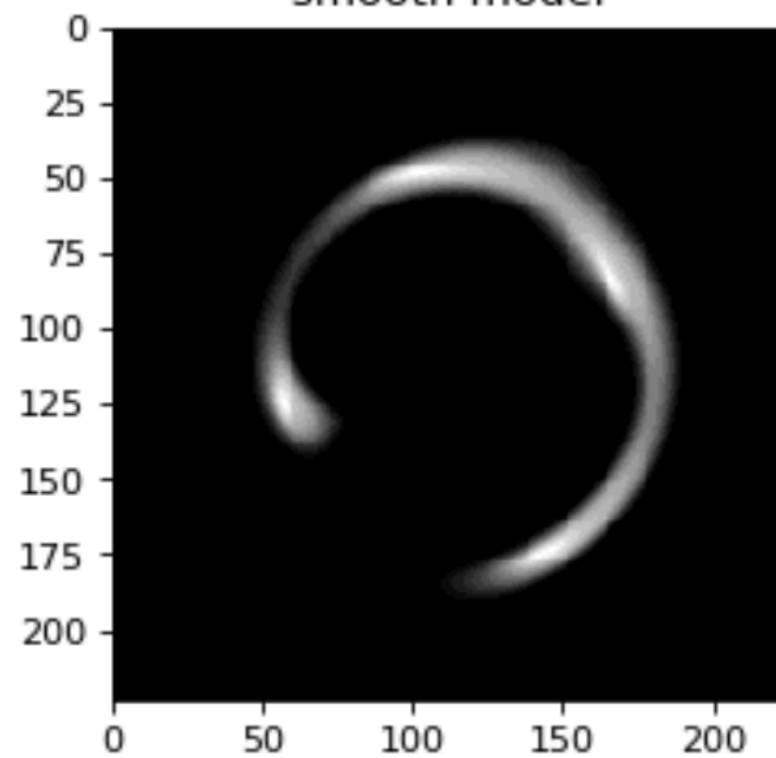




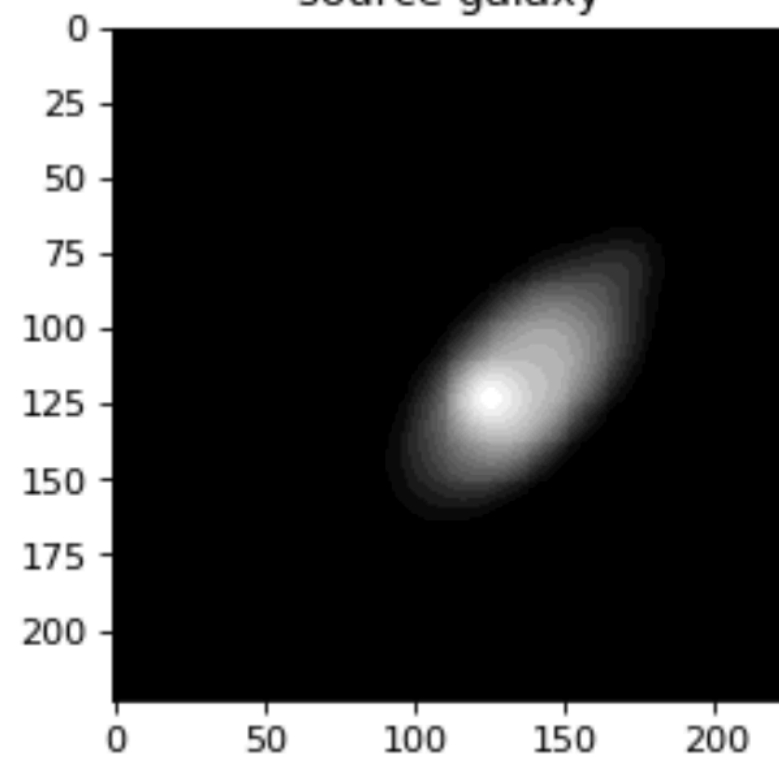
lensing image



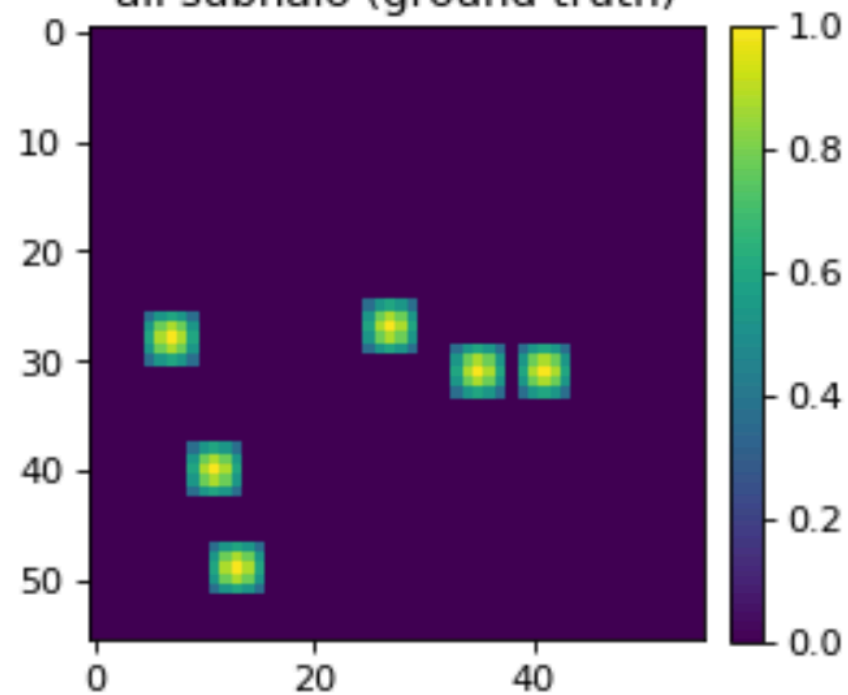
smooth model



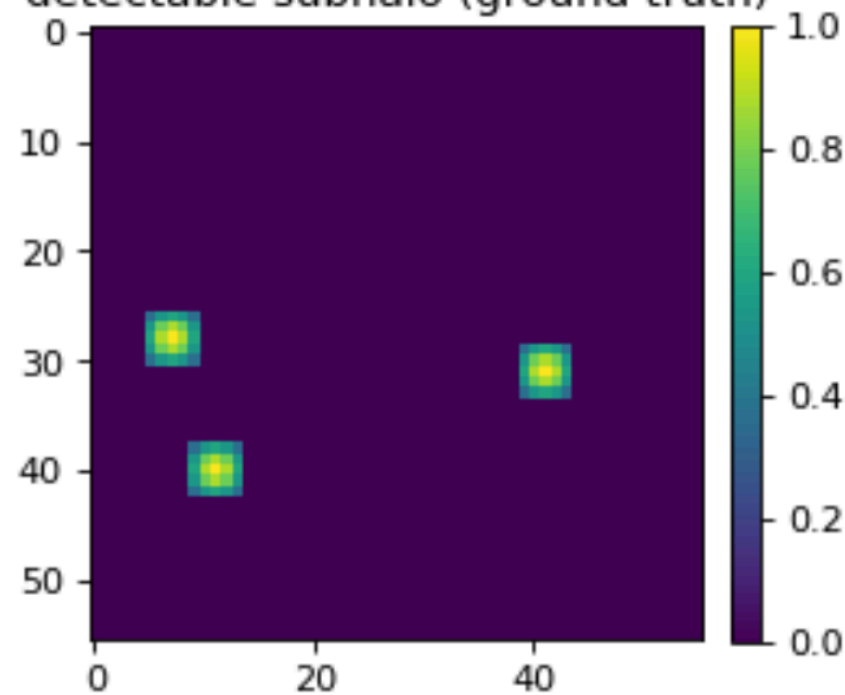
source galaxy



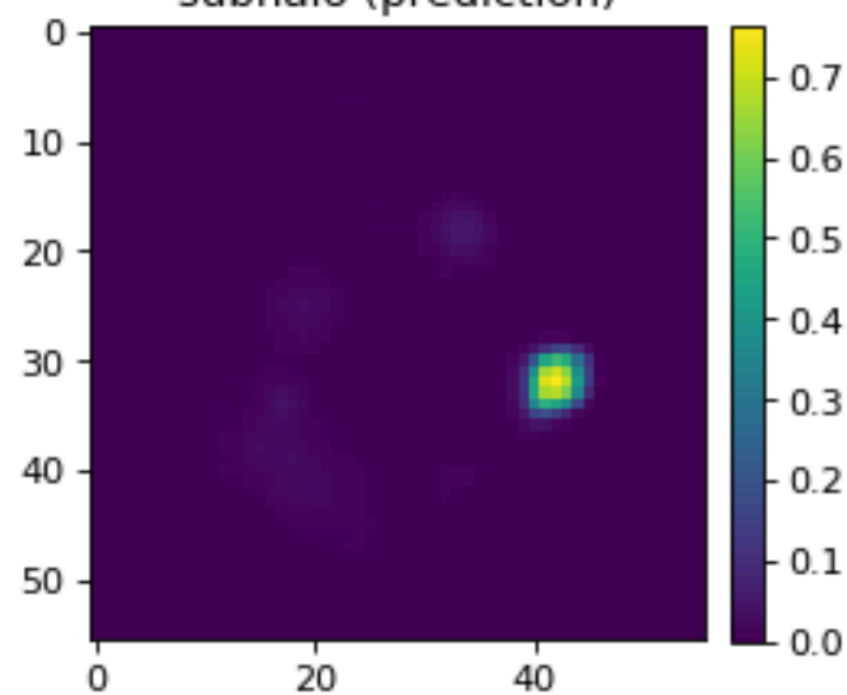
all subhalo (ground truth)



detectable subhalo (ground truth)



subhalo (prediction)





# Summary for this project

- Deep learning shows some promising result in dark matter substructures detection in lensing.
- “rejections” for no subhalos around the strong lensing arc.
- “detections” and “regression” for subhalos around the strong lensing arc.
- Learning from the NN output might also be interesting (intuitive physics), should be investigate more.
- Generating more realistic simulated data and analyzing real data would be coming soon!



# Thank you!



**Image Credit: Hubble/STScI & NASA**